

QUANTIFICATION OF RISK FACTORS

FOR

OCCUPATIONAL CARPAL TUNNEL SYNDROME

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by

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DEDICATION

To my family whose support and love helped me become what I am today

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I dedicate this thesis to my old friends at home and alumni of 86' Horticulture, Korea University.

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ABSTRACT

Carpal tunnel syndrome (CTS) is a common type of neuropathy in which the median nerve is compressed within the carpal tunnel at the wrist. The incidence of carpal tunnel syndrome in the work place is called occupational carpal tunnel syndrome (OCTS). OCTS is a multifactorial cumulative trauma disorder. This disorder is linked to occupational factors, clinical factors, and personal factors. Our objective is in quantifying factors and predicting the incidence of OCTS. Statistical procedures, back propagation method of neural network, and fuzzy aggregate operator have been adapted to quantify factors and predict the incidence of OCTS.

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CHAPTER 1

INTRODUCTION

1.1 Occupational Carpal Tunnel Syndrome (OCTS)

Carpal tunnel syndrome (CTS) is a common type of neuropathy in which the median nerve is compressed within the carpal tunnel at the wrist [Dawson et al., 1983]. The eight carpal bones and the strong band of the transverse carpal ligament create the carpal tunnel. Contained within this narrow, confined space are the median nerve, its vascular supply, and nine extrinsic flexor tendons of the fingers [Tountas et al., 1983]. When the wrist is flexed or extended, the carpal bones and flexor retinaculum exert a resultant force on the flexor tendons and median nerve. This force could directly compress the median nerve or inflame the tendons or their sheaths [Armstrong & Chaffin, 1979].

These flexions and extensions of the wrist happen thousands of times in our daily life. In the work place, tasks, jobs, and productivity concerns require more frequent and forceful exertions on the wrist than any other time. The incidence of carpal tunnel syndrome (CTS) in the work place is called occupational carpal tunnel syndrome (OCTS). The increase of OCTS can largely be blamed on the widespread industry shift to faster forms of automation [Barrer, 1991]. The expansion and inclusion of global markets have forced American

businesses to develop more efficient production methods and advanced technology to remain competitive. New types and specialization of jobs, higher physical demands on existing job tasks, and higher expectation of employee performance all contribute to biomechanical stresses not encountered in the past. Increased work loads, at faster production speeds, with little variation, all contribute to the problem of repetitive trauma which is associated with the development of CTS [Siebenaler & McGovern, 1992].

1.2 Risk Factors and Symptoms of Carpal Tunnel Syndrome (CTS)

CTS is a multifactorial cumulative trauma disorder. This disorder is linked to occupational factors, clinical factors, and personal factors. Occupational factors include highly repetitive and highly forceful tasks or motions, and extreme postures in work place. Clinical factors include pregnancy, diabetes, and rheumatoid arthritis. In addition to those clinical factors, natural and habitual factors are considered as personal factors. Natural factors include gender, size of wrist, height, weight, and age. Habitual factors are smoking, alcoholism, and vitamin use, etc. Natural and habitual factors do not seem to cause CTS, but vary the chances of CTS incidence.

Symptoms of CTS are numbress, tingling. pain, weak grip, and loss of sensory feedback. These symptoms result from motor and sensory impairment of the nerve through the carpal tunnel. Symptoms of CTS vary among individuals, and are mostly uncomfortable enough at

night to wake the patient. As the condition progresses, the worker may experience swelling and soreness in one or both hands, recurring headaches and shoulder pain, and inability to distinguish between hot and cold. The autonomic nerve impairment characteristic of CTS often results in loss of sweat function. The moistness of the hand is an important factor of friction and affects the ability to grasp and manipulate objects, and the lack of it results in the loss of manual dexterity [Morgan, 1990].

1.3 Occupation and Statistics of the Incidence of Occupational Carpal Tunnel Syndrome

Meat packing and poultry processing industries demonstrated 10 times greater risks than the overall industry average [Hanrahan, 1991]. Dental hygienist, data entry clerks, assemblers, hand cutting operator, machine operator, and grocery checking clerk are the occupations for which incidences of OCTS have been reported. In addition to those occupations, sheep shearers [Monsell & Tillman, 1992] and sign language interpreters [Stedt, 1992] have been reported to have an association with OCTS. Any occupation, which requires repetitive and forceful tasks, vibrations and cold temperature to the wrist, increases the incidence of OCTS.

There were 7,926 incident OCTS claims identified for the years 1984-1988 in Washington state. The mean age was 37.4 years and female ratio was1.2:1 in this population [Franklin et al., 1991].

Treatment for OCTS - including surgery and recovery-time lost from the job, as well as worker replacement and diminished productivity can be costly. It has been estimated that the average company with a high risk for worker injury due to repetitive motion will spend \$250,000 per year, per 100 employees. In Wisconsin State, 8,595 cases have been reported and compensated from 1983 to 1988. These costs of compensation and medical treatment amounted to \$33 million [Hanrahan, 1991].

1.4 Recommendation, Research Methods and Trend on Carpal Tunnel Syndrome.

To reduce the incidence of carpal tunnel syndrome, industrial hygienists and researchers recommend reduction of repetition and force, proper posture, right tool selection for each individual, use of arm or wrist supports and job rotation. There can be many more recommendations to reduce and prevent OCTS coming from different experts.

Biomechanical, ergonomic and epidemiological studies have been conducted to understand and reduce the incidence of carpal tunnel syndrome. Biomechanical and ergonomic studies help researchers to understand the mechanism of the wrist during motion, and to improve work environments and redesign the job schedule and task. Epidemiological studies compare between general population and CTS-controlled groups, and search for any significance among

occupational factors, natural (gender, age, height and weight, etc) and habitual (smoking, alcoholism, and use of any medicine, etc) factors. Electromyography activity of musculature measurement (EMG), nerve conduction time (NCV) and ergonomic on-site inspection and intervention are common tools of researchers. Questionnaires and interviews are usual methods to collect personal data and assigned tasks. As analytical methods of measurement and data collection, statistical procedures are most common and well-supported.

Recently, there have been many studies to quantify occupational factors (tasks and jobs) by a predictable index. Other studies have shown that the changes in production rate can reduce the incidence of OCTS while keeping proper productivity [Fisher et al., 1990], and a computerized system can assist to formulate wrist motions under stress, based on mathematical models. [Fischer et al., 1990].

1.5 Summary of Thesis

As mentioned above, the trend of research is quantifying and setting mathematical models to predict the riskiness of jobs and tasks, and prevent occupational carpal tunnel syndrome. If we consider this situation as finding the relationship between the input space and the output space of our world, we may use new numerical methods which have certain advantages. Human beings of intelligence face the situation of considerable inputs and criteria for decision making. Human beings learn to recognize the relationship or map between

inputs and output and make decisions based on the learned knowledge (relationship) and information. In the research of OCTS, there are many inputs and outputs which can be mapped to each other to meet our objective - quantifying factors and predicting the incidence of CTS. Statistical procedures are used to examine these mapping. Recent approaches of artificial intelligence, neural network and fuzzy set theory, are also used to examine these mappings. The back propagation method of neural network and the fuzzy aggregate operator have been adapted to predict OCTS. Dr. Grant has generously allowed us to use her data [Grant, 1992] for further analysis.

1.6 Layout of Thesis

In chapter 2, factors of CTS will be reviewed in detail.

In chapter3, the basic assumption for the quantification of factors will be suggested.

In chapter 4, the result of the statistical procedure will be shown and discussed.

In chapter 5, back propagation of neural network is presented as another quantifying model and predicting indicator.

In chapter 6, aggregation by fuzzy connectives is represented with hierarchical structure. Aggregation combined with back propagation networks is presented as the final model.

In chapter 7, the conclusion and further study will be discussed.

CHAPTER 2

BACKGROUND

2.1 Occupational Carpal Tunnel Syndrome

Carpal tunnel syndrome (CTS) is a common type of neuropathy in which the median nerve is compressed within the carpal tunnel at the wrist. CTS is one of cumulative trauma disorders (CTDs) which is also called 'repetitive strain injury (RSI), upper body pain syndrome, nerve entrapment syndrome, and peripheral nerve dysfunction.' [Gerwatowski, 1992] The incidence of CTS in work place or due to tasks is called 'occupational carpal tunnel syndrome.'

2.2 Anatomy of Carpal Tunnel and Pathphysiology of CTS

The eight carpal bones and the strong band of the transverse carpal ligament create the carpal tunnel. Contained within this narrow, confined space are the median nerve, its vascular supply, and nine extrinsic flexor tendons of the fingers [Dawson, 1983]. Figure 2.1 [Skandalakis, 1992] shows a sectional diagram of the carpal tunnel and its related anatomical structures. Figure 2.2 shows the median nerve which gets pinched in CTS. Figure 2.3 and 2.4 show opposite views of the tight compartment consisting of strong bones and ligaments. During the flexion and extension of the wrist, the carpal bones and

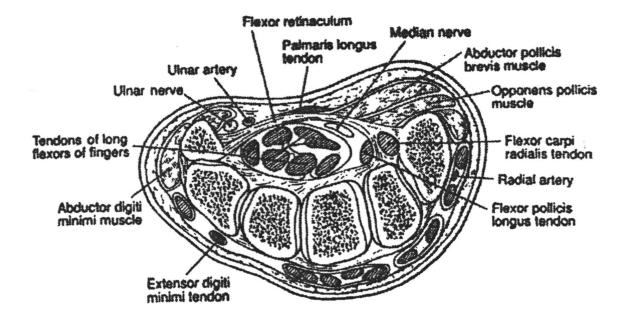


Figure 2.1 Sectional Diagram of Carpal Tunnel (Adapted from Skandalakis et al., 1992)

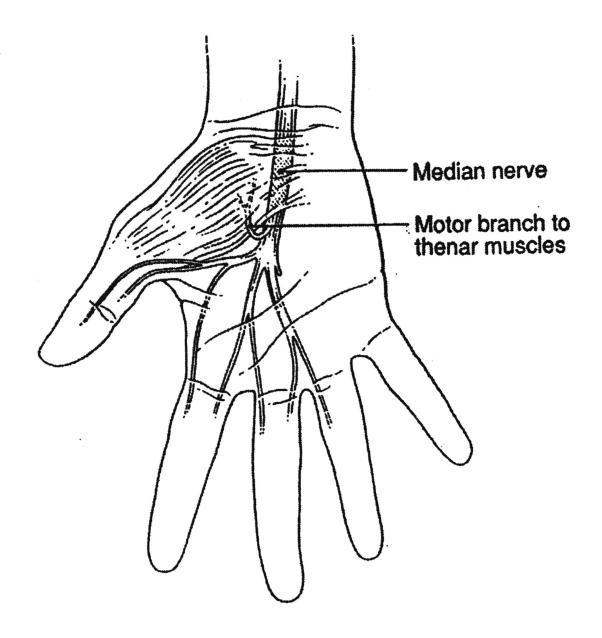


Figure 2.2 Median Nerve in Hand (Adapted from Skandalakis et al., 1992)

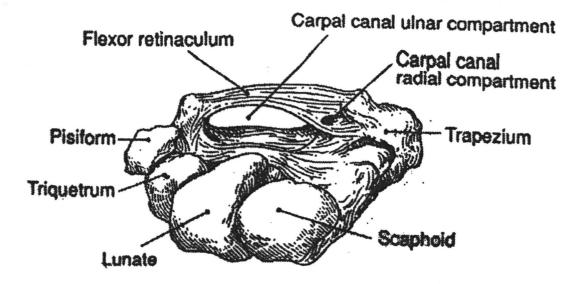


Figure 2.3 Proximal View of Carpal Canal (Adapted from Skandalakis et al., 1992)

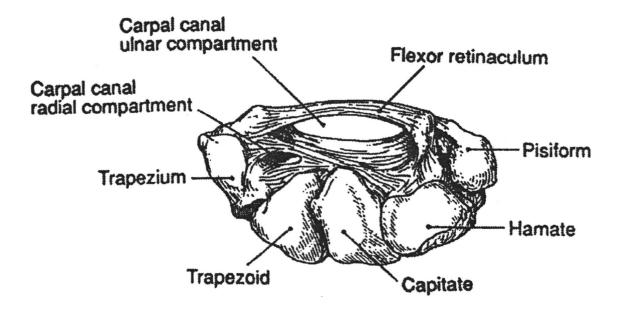


Figure 2.4 Distal View of Carpal Canal (Adapted from Skandalakis et al., 1992)

flexor retinaculum exert a resultant force on the flexor tendons and median nerve. This force may directly compress the median nerve or inflame the tendons or their sheaths in the wrist [Armstrong & Chaffin, 1979]. This compression, which is generated by an external force on inflamed tendons and sheaths, increases pressure in the carpal tunnel. Gelberman et al. show that the normal pressure was 2.5 mmHg, and the pressure in patients was 32 mmHg. During the 90° flexion and extension, those pressures increased to 30 mmHg in normal subjects and 94 mmHg in CTS patients [Gelberman, 1981]. Rydevik et al. show that the increase of pressure to nerves will result in the slowing of interneurial blood flow in venules [Rydevik, 1991]. This continuous vascular insufficiency will lead to anoxia and damage to the capillary endothelium, resulting in epineurial edema [Omer, 1992]. Continued congestion will block the axoplasmic transport system, resulting in disturbances in the nerve conduction. This disturbances in the nerve conduction will result in dysfunction, pain, and symptoms of the wrist.

2.3 Recommendation, Research Methods and Trend on Carpal Tunnel Syndrome.

To reduce the incidence of carpal tunnel syndrome, industrial hygienists and researchers recommend reduction of repetition and force, proper posture, right tool selection for each individual, use of arm or wrist supporter and job rotation. Since high repetition and force are major causes, the reduction of repetition and force is a very

effective solution to OCTS, by slowing the production rate and the use of mechanical equipment which aid human worker. Since bad postures are worsening the situation of OCTS, the re-design of the work place and the tasks can improve the situation. Also, the right tool selection for each individual has the advantage of reducing unnecessary force in the handling of tools. The use of arm or wrist supports prevent excessive flexion or extension of the wrist and direct pressure on the palm. Job rotation gives workers break times to rest the wrist and variation of tasks in daily working hours.

There can be many more recommendations to reduce and prevent OCTS from different experts. Early discovery of CTS will make it easier to treat. For more organized efforts, the company can hire an industrial hygienist or engineer to launch the ergonomic programs and educate managers and workers. From medical and epidemiological aspects, better and nationwide surveillance program of CTS can be required for precise information and data collection which are crucial in identifying risk factors.

Biomechanical, ergonomic and epidemiological studies have been conducted to understand and reduce the incidence of carpal tunnel syndrome. Biomechanical and ergonomic studies help researchers to understand the mechanism of the wrist during motion, improve work environments, and redesign job schedules and tasks. Armstrong and his research team have shown [Armstrong, 1979] a biomechanical model of the wrist for analyzing cumulative strain in tendons and tendon sheaths, and for studying muscle response to

reaction forces of hand tools. Moore et al. have shown a quantified biomechanical model based upon force, motion and posture over the duration of the tasks [Moore et al., 1991].

Epidemiological studies compare between general population and CTS - controlled or exposed group [Morgenstern, 1991], and search for any significance among occupational factors, natural and habitual factors. Electromyographic activity of musculature measurement (EMG), nerve conduction testing (NCV), and ergonomic on-site inspection and intervention are common tools of researchers conducted in the following industries: poultry processing plant [Armstrong et al., 1982], electronic assembly plant [Feldman et al, 1987], window hardware manufacturing plant [Burt, 1991], and fiberglass manufacturing plant [Grant, 1992]. Clinical testings for CTS include the pressure provocative test, Phalen's test, and Tinel's sign, which do not require hardware like EMG and NCV testing. EMG testing requires the placement of electrodes in the muscle to observe any abnormality. Nerve conduction time testing requires the placement of electrodes along the nerve to observe the slowness of electricity velocity.

In the pressure provocative test, direct thumb pressure is applied to the volar aspect of the patient's wrist over the median nerve at the cephalad end of the carpal tunnel for 2 minutes. The reproduction of symptomatology and the relief of symptom when the pressure is removed is then observed [Williams et al., 1992]. Phalen's test is to hold the hand with the wrist in complete palmar flexion with

elbows extended and forearms pronated, and to check the time for the occurrence of symptomatology. Tinel's test is to tap over the median nerve at the cephalad end of the carpal tunnel with the wrist in a neutral position and to observe for the presence or absence of tingling sensation.

Questionnaires and interviews are usual methods to collect personal data and assigned tasks. There are many criteria and categories in questionnaires and interviews. The questions are made to collect data about whether a person belongs to or is exposed to risk factors as discussed above. An example of a medical questionnaire is like the following [Delgrosso, 1991];

- Identity, including country of birth

- Educational level reached

- Former occupations

- Current occupations

- Description of occupational aspects (employment years):

Repetitive flexion-extension of the wrist

Motion of hands involving exertion of strength

Use of various hand tools (e.g., hammer, knife, staple gun)

Exposure to vibrations

knitting, painting, other handicrafts

- Time of onset of symptoms of carpal tunnel syndrome

- Cofounding factors or diseases (diabetes, rheumatoid arthritis, gout, oral contraception, others)

- Family history of carpal tunnel syndrome

As analytic methods of measurement and collected data, statistical procedures are most common and well-supported ones. Multiple linear regression, logistic regression, and ANOVA procedure are useful procedures in analyze significance of variables and difference between symptomatic group and controlled group.

Recently, there have been many researches to quantify occupational factors (tasks and jobs), using biomechanical supports. Another research shows that changes of production rate can reduce the incidence of OCTS while keeping proper productivity, and presents a mathematical model. Fischer et al. presented a computerized system for measuring wrist stress, by categorizing wrist and hand motions and formulating a mathematical equation [Fischer et al., 1990].

CHAPTER 3

ASSUMPTION and OBJECTIVE

3.1 Productivity and Prevention

Even if prevention of OCTS is the goal of the researcher and field manager, there is another goal that must be met for survival in a competitive global market. That goal is called 'productivity' in the work place. Productivity requires pre-designed production rate and scheduled achievement of workers. The requirement for productivity forces workers to finish their jobs and tasks which exceed their physical ability over time. One solution is to reduce production rate, and replace the human worker with automation.

However, these recommendations may not satisfy the goal of achieving productivity. The recommendation should be based on a reasonable quantified model or tool which accounts for occupational riskness or stress from jobs and tasks, and considers human durability against the stress. Replacement workers by full automation is only available to some jobs and tasks. Therefore, our goal is to achieve maximum yet safe productivity which reduces or prevents OCTS. Before reviewing and presenting new quantified models, the focus on tasks, the human wrist, and the clinical decision of whether a patient has CTS or not, are necessary to apply mathematical tools. The

concept of the stress from jobs and tasks, and the durability of the human worker and the wrist will be reviewed and explained.

3.2 Three quantifiable areas (factors)

In Figure 3.1, there are three major areas in which research can apply quantification. The first area (occupational factor) includes stress from tasks and jobs. The second area (personal factor) includes human layer and wrist layer. The third area (indicating factor) includes clinical and biomechanical decisions. In these areas, uncertainty and unknown relationships exist, between areas, and within each area. The application of a mathematical model will be possible and necessary for modelling the relationships within each area and between three areas.

Occupational factors (top left area) are about stress generated by tasks and jobs in the work place. Occupational factors include repetitiveness, force, posture, temperature, etc. Thus, stress can be represented as a function of repetitiveness, force and posture. This function can be a linear or non-linear relationship between inputs (factors) and output (stress). From Figure 3.1, the stresses will reach through the human layer to the wrist layer.

In the human layer, the worker will do his/her job and finish tasks. During those working hours, stress will be transferred to the wrist layer which has a certain amount of durability against stress. The amount of stress which exceeds the amount of durability will

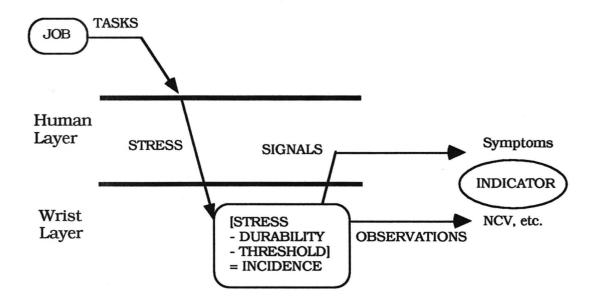


Figure 3.1 Three quantifiable areas

accumulate in the wrist layer. It will change the status of the wrist and increase the pressure on the nerve through the carpal tunnel. Beyond a certain level or threshold, the wrist layer will send signals to the human layer which are sensed as pain and numbness. The accumulation of the excess amount of stress over the durability level can occur over a short or long period of time.

At the end of the transfer line, there is the indicator layer which collects observations from the human layer and the wrist layer and decide the incidence of CTS. Researchers and medical doctors may collect data by questionnaire from the human layer and through clinical tests such as pressure provocative test, Phalen's test, Tinel's test, and nerve conduction velocity or times (NCV) from the wrist layer. Based on these information, they will decide whether a person has carpal tunnel syndrome. This decision is used for clinical decisions which often involves surgery on the wrist.

The quantification of stresses from jobs will be supported by biomechanical and ergonomic studies. The assumption and quantification of durability depends on personal factors, and will be explained and supported by epidemiological and medical researches. The quantification of indicator is based on questionnaire and clinical test. The aggregation of these questionnaires and clinical tests lead to a decision to have surgery for release of the pain in the wrist. However, the quantification has not been interpreted for the degree of the symptom severeness and the incidence of CTS. In the next section, the concepts of the entity of stress and durability, and the

useful interpolation of indicator tools for the degree of the incidence of CTS, will be explained and suggested.

3.3 The concept of Stress and Durability, and the Interpolation of Indicator tools as Degree Indicator

First, the concepts of stress of tasks and the durability of the human worker will be introduced. 'Stress' indicates a certain entity which is dependent on tasks and jobs. It does not mean the stress to the wrist (or median nerve or tendon, etc.) in biomechnical term. This stress is a quantified index (let's put 'str' as unit) based on tasks and jobs. For example, the task of 'picking a 10 pound part and inserting into a hole per 2 min' will have 23 (str) in this stress index table. Durability is defined as a certain entity which the human worker can have potential for throughout his/her life. For example, a male worker, 35 years old with no medical fracture on the wrist will have 200,000 (drb).

If the quantity of stress from tasks exceed the durability of the human worker, it will cause CTS. Let us compare to some concepts of physics.

velocity: $v = |x_b - x_e|/t$ acceleration: $a = |v_b - v_e|/t$ force: F = m apressure: $p = \frac{F}{A}$

where

 x_b is a beginning position x_e is an ending position v_b is a beginning velocity v_e is an ending position

Our task is to move object from A to B. How fast we move is related to repetitiveness. Force and bad posture can be considered as the mass of that object. Force is the product of acceleration (repetitiveness) and mass (bad posture and force to be required for job) of the object. Therefore, force in this case represents 'stress.' Since this force is applied to a certain area, it is called 'pressure'. If we consider durability as analogous to a metal sheet which can hold a certain pressure, there will be two variables needed for the sheet to keep its shape against the force. They are the material characteristics of sheet metal and the area on which the force applies. Natural factors can be considered as analogous material characteristics. Habitual and clinical factors are analogous to the size of the area on which the force applies. Under constant force (stress from tasks and jobs), a change in size of area will yield different pressure per unit area of metal sheet. In other words, a change in size may be compared to a change in human durability. For example, the aging of the worker means the decrease of durability which is analogous to the decrease of size in metal sheet.

The dimension of the entities 'stress' and 'durability' is the same as the dimension of force which is kg * m $/s^2$. It involves a time dimension. CTS is developed over time, which can be short or long.

This means that we should consider two types of excess over time. Excesses over a short time and average excesses over a long time. In Figure 3.2, an instance of an excess of stress over durability occurred and can explain the incidence of OCTS over 1 - 5 years.

Figure 3.3 (a) shows a case where the instance of excess did not happen. In Figure 3.3 (b), after averaging stress over time, average stress exceeded the deteriorating durability over age and other factors. From this assumption, two types of excess, instance and average excesses, should be considered and used for explanation of the incidence of OCTS. In Figure 3.4, the sudden decrease in durability is precipitated by a broken bone, or other trauma.

Since stress and durability have multiple variables, they are functions of multiple inputs which are not known. Three dimensional presentations can be helpful in understanding these functions. In Figure 3.5 (a), the z-axis, x-axis and y-axis represent stress, force and repetition, respectively. At the region of high force and repetition, stress is highest. In Figure 3.5 (b), the z-axis, x-axis and y-axis represent durability, age and gender, respectively. In gender, there are two categories - male and female. If we consider gender as the difference of physical strength, rather than biological difference, gender can be represented as a continuous entity between categories and within group. The male has more durability than the female, and the younger person has more durability than the older one. When these two surfaces are combined by conceptually subtracting durability from stress, the result will look like Figure 3.6 (a). If we further

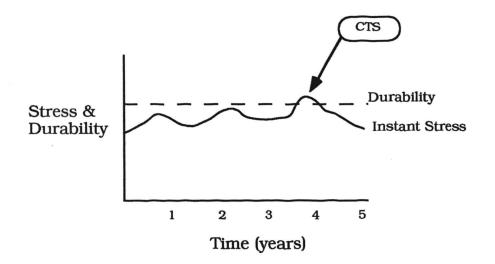


Figure 3.2 Instance stress excessiveness over durability

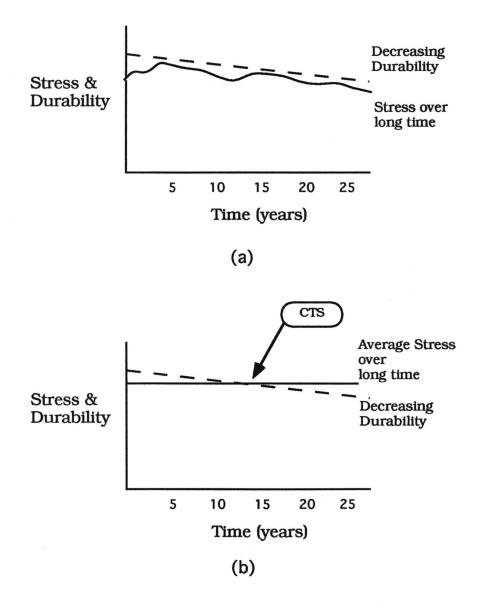


Figure 3.3 Long period stress over durability

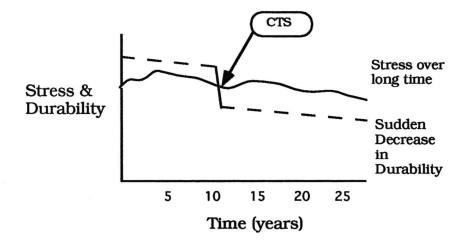


Figure 3.4 Sudden decrease of durability

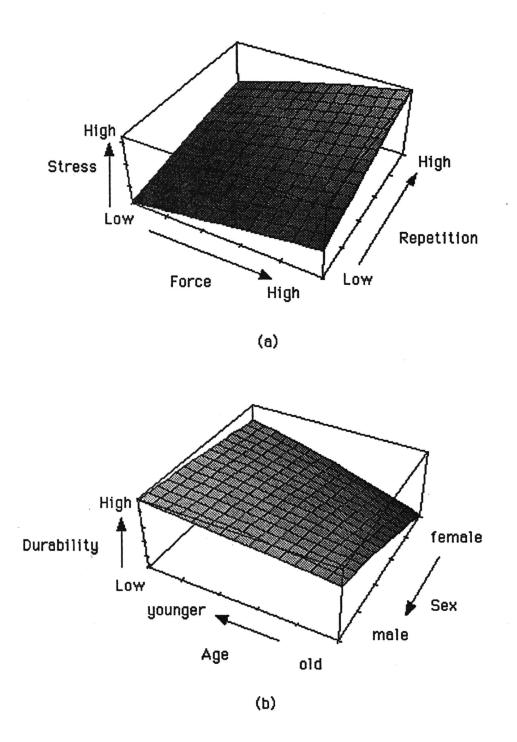
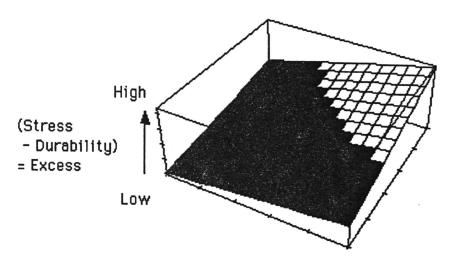
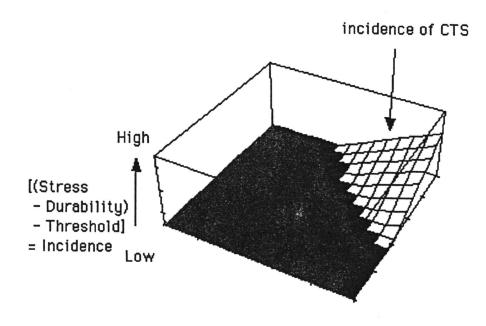


Figure 3.5 Three Dimensional Presentation of Stress and Durability



(a)



(b)

Figure 3.6 Three Dimensional Presentation of Durability, Stress, Excess, Threshold, and Incidence

subtract the threshold value which humans can tolerate, we will get the surface in Figure 3.6 (b), which represents the incidence of CTS.

The surface of Figure 3.6 (b) represents the excessiveness of stress over durability and threshold. The question is how to measure the amount of excessiveness from the human worker and the wrist. As mentioned above, the researcher and medical doctor will use questionnaire and clinical test, respectively. Their interests are in identifying the person who has symptoms and to determine whether the person needs surgery and compensation. The decision can be a yes or no response, but can not determine the severity of the carpal tunnel syndrome. The data collection by questionnaire is subjective, while clinical tests have imperfect credibility [Williams, 1992] to determine the CTS patient. If we consider the questionnaire and the clinical tools as evidences for the decision of whether a patient has CTS, we can aggregate evidence from them and create measures of the degree of credibility. Then, we may assume that we can interpret the degree of credibility as a measure of the degree of progression or incidence of CTS.

NIOSH has guidelines [Franklin, 1991] for the decision of whether a patient has CTS. Its criteria is that if a person satisfies one of the condition, then he/she is considered an OCTS patient. This means that the evidence is integrated by a logical OR condition. If we consider the aggregation of evidence problem, we can give more credibility to a decision which is supported by as many evidences as possible. The above idea will not affect any determination of whether a

patient has CTS, but will give a different point of view for a different purpose, which is the determination of the degree of CTS progression and excessiveness.

3.4 Objectives and Methodology

Statistical procedures are well known and structured for analysis of relationship between inputs and output. These procedures can decide the significance of inputs (independent variables) on the output (dependent variable). However, such procedures can not fully support the idea which is presented above. Usually, statistical procedures are used for the determination of the significance of the independent variable or correlations, not for predicting the possible progression and incidence of OCTS. Two statistical procedures have been used in biomechanical research and epidemiological studies: Linear regression and Logistic Regression These procedures will be explained in Chapter 4. One of those research data has been obtained [Grant, 1992]. In Dr. Grant's study, the purpose is to determine whether the NCV test and other variables are related significantly. Her data was restudied for two statistical procedures, and presented in chapter 4.

Since the objective of this study is to quantify OCTS factors and predict the possible incidence of OCTS, additional mathematical methods will be tried based on the above assumptions:

1) Three quantifiable areas - stress from the job, durability of human worker, and indicator of severity and progression.

2) Aggregation of the evidences from each quantifiable area and final aggregation between the three areas.

The back propagation method of neural network will be used to train the network, given inputs (evidences) and outputs (decisions), and predicting the output from test inputs. The Jack and Knife procedure will divide the data set into training patterns and test patterns.

The fuzzy aggregation operator can aggregate the evidences of the three quantifiable areas within a continuous range of [0,1] which can support the above assumptions: an indicator for the degree in stress, durability, and severity of incidence. The advantage of aggregation from fuzzy set theory will be combined with the advantage of back propagation from neural network for training and predicting in a combined model.

CHAPTER 4

STATISTICAL ANALYSIS

4.1 Description of Data from Dr.Grant

Raw data provide these information.

PART	Participant number			
SYMP	Whether or not the observation was regarded as CTS			
	symptomatic (1=yes, 0=no)			
AGE	Age (in years)			
DOM	Dominant or non dominant hand (1=dominant,			
	0=nondominant hand)			
MED	Vibration threshold measured in third (middle) finger (in			
	vibration units)			
NCV	Motor nerve conduction time measured in the median			
	nerve (in milliseconds)			
SEX	Male or female (1=male, 0=female)			
VIT	Whether or not the participant reported vitamin use			
	(1=yes, 0=no)			
ALC	Whether or not the participant reported using alcohol			
	(1=yes, 0=no)			
000	Occupation (1=production, 0=other)			
YRS	Years working in present job			
SMO	Whether or not the participant smoked (1=yes, 0=no)			
HT	Height (in inches)			

WT Weight (in pounds)

ART Whether or not the participant had been diagnosed with arthritis (1=yes, 0=no)

S Whether or not the participant had ever had surgery or broken bones in the hand or wrist (1=yes, 0=no)

4.2 Dr. Grant's Study

In Grant's study "Age and Weight Effects on Motor Nerve Conduction Time Measures in an Asymptomatic Industrial Population" [Grant, 1992], a cross-sectional study of 77 industrial workers was performed to determine the relationship between median motor nerve conduction time at the carpal tunnel and select personal factors. As a measurement tool, the digital electroneurometer, a hand-held, battery-powered device was used. Multiple linear regression was used to analyze the significance of these factors to Nerve Conduction Time (NCV). The reason for investigation in Nerve Conduction Time was that in patients with carpal tunnel syndrome (CTS), motor conduction delay had been demonstrated in many researches. Also, other studies had shown that aging factor has an effect on slowing nerve conduction.

Grant's multiple linear regression model was:

Nerve Conduction Time = function of (Age, Gender, Hand dominance, Height, Weight, Length of employment, Occupation, Smoking) [4.1]

Indicator variables (0 or 1) were used for gender, hand dominance, occupation, and smoking. Stepwise linear regression analysis was used for developing best fit equations. The software SAS systems was used for data analysis.

The stepwise variable selection procedure (at a significance level of p = 0.05) indicated that three variables - age, years of employment and weight - should be included in the model. However, the R-Square of the model was 0.2028, which is not enough to account for the dependent variable 'Nerve Conduction Time'. On the next four pages, the study group characteristics (Table 4.1), participant occupation descriptions (Table 4.2), criteria for study participation (Table 4.3) and results of stepwise regression procedure (Table 4.4) are shown.

4.3 Objective and Layout of Statistical Analysis

As mentioned in chapter 3, nerve conduction time (NCV) and symptom (SYM) are indicators of CTS. One of our interests is to find or understand the relationships between risk factors and indicators. Statistical analysis can find the relationships between variables, and the significance of independent variables to the dependent variables, NCV and SYM. For the dependent variable 'NCV', multiple linear regressions were performed as Dr. Grant did in her study. For the dependent variable 'SYM', logistic regressions were performed because its response level is binary or dichotomous. During the preparation of data sets, it was found that exactly the same data set as

Total number of participants	77	
Males	41	
Females	36	
Production workers (hourly)	51	
Professional/support staff	26	
Age (years):		
Mean \pm std dev.	34.7±8.1	
Minimum	22	
Maximum	66	
Length of employment (years):		
Mean \pm std dev.	4.9±3.1	
Minimum	0.8	
Maximum	14.0	
Height:		
Mean \pm std dev. (inches)	67.8±4.2	
(cm)	172.2 ± 10.7	
Minimum (inches / cm)	59 / 150	
Maximum (inches / cm)	77 / 195	
Weight:		
Mean \pm std dev. (lbs)	163.7±38.1	
(kg)	74.3 ± 17.3	
Minimum (lbs / kg)	90 / 41	
Maximum (lbs / kg)	270 / 122	
Number of smokers	16	

Table 4.1 Study Group Characteristics

Table 4.2 Participant Occupation Descriptions

Title	Tasks	Associated Risk Factors for Upper
IIIIe	TASKS	Extremity CTDs
Bushing	- Monitor glass flow through bushing	- Frequent (est. 3,200 daily) ulnar and
		radial wrist deviation.
Operator	tunnels. Keep strands separated.	
	- Use spray nozzle to keep glass cool.	- Occasional (est. 550 daily) overhead
	- Activate overhead controls.	grasps and reaches.
		- Occasional (est. 660 daily) force
		application with the hand.
Winding	- Lift spools of fiberglass (35-45 lbs)	- Frequent (est. 4,800-5,600 daily)
Operator	from spindle to carrier.	ulnar and radial wrist deviation.
	- Apply codes to spools.	- Frequent (est. 2,400 to 2,800 daily)
	- Trim waste from tubes with knife.	application of force (35-45 lbs) with
	- Use spray nozzle to keep tubes wet.	arms, wrists and back.
		- Frequent (est. 7,200 to 8,400 daily)
		manual force application.
Creel	- Locate loose strands at the end of	- Frequent (est. 9,600-11,200 daily)
(Machine)	each spool.	force application with the hand.
Operator	- Cut strands with scissors.	- Frequent (est. 2,400-2,800 daily)
	- Tie strands in knots.	application of force (35-45 lbs) with
	- Lift spools from carrier to conveyor.	arms, wrists and back.
		- Frequent (est. 4,800-5,600 daily) use
		of pinch grips.
Packer/	- Fold cardboard boxes and applies	- Frequent (est. 9,600-11,200 daily)
Inspector	stickers.	wrist flexion and extension.
mopector	- Remove cardboard tubes from spools	- Frequent (est. 2,400-2,800 daily) force
	with small pneumatic tools.	application with the base of the palm.
	- Wrap spools in plastic, twists & ties	- Frequent (est. 1,200-1,400 daily) force
	packages closed.	application (35-45 lbs) with the
	- Place spools in boxes.	shoulders, wrists and back.
Data Entry	Use computer keyboard and numeric	- Frequent (est. 10,000 daily)
Clerk/	keypad.	application of force with the fingers,
Secretary	ncypau.	with wrists flexed, and the neck bent to
Secretary		one side.
Laborator	Derform quality control tests	
Laboratory	- Perform quality control tests.	- Occasional use of pinch grips (varies
Technician		daily).
Engineer/	- Review engineering drawings and	- Occasional force application with
Systems	production reports. Perform analyses	the fingers (typing).
Analyst	using computer software.	

Table 4.3 Criteria for Study Participation

- No history or prior diagnosis of CTS.
- Negative Phalen's and Tinel's signs.
- No complaints of numbress, tingling or pain in the hands or fingers.
- No history or prior diagnosis of Raynaud's syndrome.
- No history bones in the hand or wrist.
- No prior hand/wrist surgery.
- No history or prior diagnosis of arthritis.
- No history of kidney, glandular, or metabolic disorders.
- No history of diabetes.
- No history of heart disease or circulatory disorder.
- Not pregnant, nor pregnant within the last year.

variable	Estimate	Std. Err.	F	Prob > t
Age	0.0138	0.0068	4.14	0.0437
Years in job	0.0461	0.1625	8.03	0.0053
Weight	0.0046	0.0012	14.81	0.0002

Table 4.4 Results of Stepwise Regression Procedure Using NerveConduction Time as the Dependent Variable

Dr. Grant's could not be recovered from raw data. In each section, the preparation of data sets will be explained.

First, the same procedures - multiple linear regression and stepwise variable selection - were performed with data set A (152 hands or wrists). Data set A is shown in the appendix. The dependent variable was nerve conduction time and the independent variables were age, hand dominance, sex, occupation, years on the job, smoking, height, and weight.

Second, multiple linear regression and stepwise variable selection were performed with data set B (252 hands or wrists). Data set B is shown in the appendix. The dependent variable was nerve conduction time and the independent variables were age, hand dominance, sex, occupation, years on the job, smoking, height, and weight. In addition to those independent variables, symptom, vitamin use, alcohol consumption, arthritis, and surgery or broken bones were added to model. All of the added independent variables were indicator variables with values of 0 or 1.

Third, logistic regression was used for the analysis of symptom as a dependent variable (response level was 0 or 1). The independent variables were age, hand dominance, sex, occupation, years on the job, smoking, height, weight, vitamin use, alcohol consumption, arthritis, and surgery or broken bones. The data set (n=252 hands) was the same as the second one in multiple linear regression.

Fourth, an experimental design procedure was performed with the same data set to see the relationships between treatments and responses. In this case, treatments were indicator variables and responses were continuous variables.

4.4 Multiple Linear Regression for Nerve Conduction Time with Data Set A (n=152)

4.4.1 Purpose

The purpose of this trial was to repeat the same procedure with same data set from Dr. Grant's study. However, the prepared data set was not matched with Dr. Grant's. The original raw data set had 133 participants (n=266 hands). Among them, 7 participants were missing values of year or height or weight. Therefore, the useful data were 252 hands of 126 participants. In her data set, she excluded the participants who had symptom, arthritis and surgery or broken bones. The number of those participants was 50 persons (100 hands). Finally, the data set consisted of 76 participants (n = 152 hands) who did not symptom, arthritis, and surgery or broken bones.

4.4.2 Preparation

Correlations between variables: PROC CORR; [4.4.1]

Multiple linear regression model:

Nerve conduction time = function of (age, height, weight, length of employment, gender, hand dominance, occupation, smoking) [4.1]

and calculate R-Square and select the best four models from each group prepared according to the number of independent variables. Also, get c(p) and MSE values for each model.

PROC REG;

```
MODEL NCV = AGE DOM SEX OCC YRS SMO HT WT/
SELECTION=RSQUARE BEST=4 CP MSE; [4.4.2]
```

Stepwise (forward and backward) variable selection procedure: entry level(SLE) p=0.05 and staying level(SLS) p=0.05 PROC REG;

MODEL NCV = AGE DOM SEX OCC YRS SMO HT WT/ SELECTION=STEPWISE SLE=0.05 SLS=0.05; [4.4.3] MODEL NCV = AGE DOM SEX OCC YRS SMO HT WT/ SELECTION=FORWARD SLE=0.05; [4.4.4] MODEL NCV = AGE DOM SEX OCC YRS SMO HT WT/ SELECTION=BACKWARD SLS=0.05; [4.4.5]

4.4.3 Results and Conclusion

Simple statistics provide mean, standard deviation, sum, minimum and maximum of each variable (Table 4.5). It shows that this data set is slightly different from Dr. Grant's data (Table 4.1). See Table 4.6 for comparison.

Total number of participants	76
Males	42
Females	34
Production workers (hourly)	53
Professional/support staff	23
Age (years):	
Mean \pm std dev.	33.4±7.6
Minimum	22
Maximum	60
Length of employment (years):	
Mean \pm std dev.	5.3 ± 5.6
Minimum	1.0
Maximum	35.0
Height:	
Mean \pm std dev. (inches)	68.0±4.4
(cm)	171.7 ± 10.6
Minimum (inches / cm)	59 / 150
Maximum (inches / cm)	77 / 195
Weight:	
Mean \pm std dev. (lbs)	166.0±38.9
(kg)	75.0±17.2
Minimum (lbs / kg)	97/ 43.8
Maximum (lbs / kg)	270 / 122
Number of smokers	24

Table 4.5 Simple Statistic of Data Set A (n=152)

	Dr. Grant's	Data Set A		
Total number of participants	77	76		
Males	41	42		
Females	36	34		
Production workers (hourly)	51	53		
Professional/support staff	26	23		
Age (years):				
Mean \pm std dev.	34.7±8.1	33.4 ± 7.6		
Minimum	22	22		
Maximum	66	60		
Length of employment (years):		×.		
Mean \pm std dev.	4.9±3.1	5.3 ± 5.6		
Minimum	0.8	1.0		
Maximum	14.0	35.0		
Height:				
Mean \pm std dev. (inches)	67.8±4.2	68.0±4.4		
(cm)	172.2 ± 10.7	171.7 ± 10.6		
Minimum (inches / cm)	59 / 150	59 / 150		
Maximum (inches / cm)	77 / 195	77 / 195		
Weight:				
Mean ± std dev. (lbs)	163.7 ± 38.1	166.0 ± 38.9		
(kg)	74.3 ± 17.3	75.0±17.2		
Minimum (lbs / kg)	90 / 41	97 / 43.8		
Maximum (lbs / kg)	270 / 122	270 / 122		
Number of smokers	16	24		

Table 4.6 Comparison between Dr. Grant's and Data Set A

The correlation matrix shows the possible relationships among variables. Significant negative or positive relationships (p<0.05) are presented. From Table 4.7, NCV is positively correlated to SEX, YRS, HT, and WT. AGE is negatively correlated to OCC and positively to YRS. SEX is positively correlated to NCV, HT, and WT. OCC is negatively correlated to AGE and YRS. YRS is positively correlated to NCV, AGE, and WT and negatively to OCC. HT is positively correlated to NCV, SEX, and WT. WT is positively correlated to NCV, SEX, YRS, and HT. This preliminary procedure suggest that sex, years on the job, height, and weight can be useful in estimating the nerve conduction time (NCV)

In the model selection procedure, there are three measurements to be considered for best model selection: R-square, c(p) and Mean Square Error (MSE). The bigger R-square is better. The best c(p) is equal to the numbers of selected variables in the model. A smaller MSE is better. Using the best fit model selection of SAS and considering those criteria, a couple of models can be suggested. However, the R-square is so low (around 0.20) that we may suspect the validity of this data collection. Important factors may have been missed in the design and collection of data.

The stepwise (forward and backward) procedure suggests that the final model is: NCV = function of (YRS, WT). In other word, years on the current job and weight are important factors to nerve conduction time. This result does not include AGE from the model :

	NCV	AGE	DOM	SEX	0000	YRS	SMO	НТ	WT
NCV	5			+		+		+	+
AGE					-	+			
DOM							1		
SEX	+							+	+
OCC		_				-			
YRS	+	+			-				+
SMO									
HT	+			+					+
WT	+			+		+		+	

Table 4.7 Correlation between Variables (Data Set A, n=152)

NCV = f(AGE, YRS, WT) of Dr. Grant. The difference may result from different data sets.

4.5 Multiple Linear Regression for Nerve Conduction Time with Data Set B (n=252)

4.5.1 Purpose

The purpose of this trial was to find significant variables to NCV, including symptom (SYMP), vitamin use (VIT), alcohol consumption (ALC), arthritis (ART) and surgery or broken bones (S). As mentioned above, all the data except data of missing values (n=252) has been used for analysis.

4.5.2 Preparation

Correlations between variables:

PROC CORR; [4.5.1]

Multiple linear regression model:

Nerve conduction time = function of (age, height, weight, length of employment, gender, hand dominance, occupation, smoking, symptom, vitamin use, alcohol consumption, arthritis, surgery) [4.2]

and calculate R-Square and select best four models from each group which is prepared by the number of independent variables. Also, get c(p) and MSE values for each model.

MODEL NCV = SYMP AGE DOM SEX VIT ALC OCC YRS SMO HT WT ART S/ SELECTION=RSQUARE BEST=4 CP MSE; [4.5.2]

Stepwise (forward and backward) variable selection procedure: entry level(SLE) p=0.05 and staying level(SLS) p=0.05PROC REG;

MODEL NCV = SYMP AGE DOM SEX VIT ALC OCC YRS SMO HT WT ART S/ SELECTION=STEPWISE SLE=0.05 SLS=0.05; [4.5.3] MODEL NCV = SYMP AGE DOM SEX VIT ALC OCC YRS SMO HT WT ART S/ SELECTION=FORWARD SLE=0.05; [4.5.4] MODEL NCV = SYMP AGE DOM SEX VIT ALC OCC YRS SMO HT WT ART S/ SELECTION=BACKWARD SLS=0.05; [4.5.5]

4.5.3 Results and Conclusion

Simple statistics provide the mean, standard deviation, sum, minimum and maximum of each variable.

The correlation matrix shows the possible relationships among variables. Significant negative or positive relationships (p<0.05) are presented. From Table 4.8, NCV is positively correlated to SYMP, AGE, SEX, YRS, HT, and WT. In other words, symptom, age, sex, years on the job, height and weight can be useful to account for nerve conduction time.

	NCV	SYMP	AGE	DOM	SEX	VIT	ALC	occ	YRS	SMO	HT	WT	ART	s
NCV		+	+		+				+		+	+		
SYM	+		+											
AGE	+	+			-		-	-	+		-		+	
DOM		· ·												
SEX	+		-			+	+	+			+	+	-	
VIT				,	+						1.4		-	
ALC			_		+			+						
occ			_		+		+		-	+			_	
YRS	+		+					-				+		
SMO								+						+
нт	+		-		+							+		
WT	+				+				+		+			
ART			+		-									
s										+				

Table 4.8 Correlation between Variables (Data Set B, n=252)

In the model selection procedure, R-square is low (below 0.20) so that we may suspect the validity of this data collection. It might be missing some important factors in design and collection of data.

Stepwise (forward and backward) procedure suggests that symptom (SYMP), vitamin use (VIT), and weight (WT) are important factors to nerve conduction time (NCV). The result does not agree with the preliminary analysis of the correlation matrix. It can be explained by the fact that correlation matrix is generated by considering only two variables and stepwise procedure considers multicollinearity of independent variables.

The resulting multiple linear regression model for NCV is as follows:

$$NCV = 3.1834 + 0.29201 * SYMP + 0.21454 * VIT + 0.0046767 * WT$$
 [4.5.6]

The multiple linear regression model - Equation 4.5.6 - was tested using five testing sets. The five testing sets were prepared by dividing Data Set C (shown in the appendix) into five sets of 50 samples exclusively and randomly. The performance rates were 22%, 18%, 38%, 20%, and 20% (considered correct if the difference between the actual and the predicted values is less than 0.152). The average was 23.6%, which is a very low performance rate for the prediction of nerve conduction time.

4.6 Logistic Regression for Symptom (response level = 0 or 1) with Data Set B (n=252)

4.6.1 Purpose

The purpose of this logistic regression is to find the best fitting and reasonable model to describe the relationship between a response variable and a set of independent variables. Since the response variable is whether the observation is regarded as CTS symptomatic, the outcome variable (SYMP) is binary or dichotomous. To deal with this case in statistical procedures, logistic regression is commonly used for analysis. With dichotomous data, the conditional mean of the regression equation must be formulated to be bound between zero and 1. The logistic regression model satisfies this constraint. And the binomial distribution, not the normal distribution, describes the distribution of the errors and will be the statistical distribution upon which the analysis is based for binary response.

4.6.2 Preparation

The SAS package provides three procedures for logistic regression analysis: LOGISTIC, PROBIT, and CATMOD. Each procedure has some minor differences and options. However, the three procedures produce almost the same results. In this analysis, the LOGISTIC procedure was used, and occasionally the CATMOD procedure was used.

First, the variable selection begins with univariate analysis of each variable. As an example of AGE .vs. SYMP, the SAS statement is as follows:

```
PROC LOGISTIC DATA=CTS2;
```

MODEL1:MODEL SYMP=AGE; [4.6.1]

Second, stepwise variable selection was done by the following statement. The entry and removal levels of variables was set at 0.05: PROC LOGISTIC;

```
MODEL NCV = SYMP AGE DOM SEX VIT ALC OCC YRS SMO HT WT ART S/
```

SELECTION=STEPWISE SLE=0.05 SLS=0.05; [4.6.2]

Third, the multivariate model with selected variables of age, nerve conduction time, sex, height, and weight, was tested for its significance to symptom. The pre-selection of five variables was based on the univariate analysis [Hosmer, 1989]:

PROC LOGISTIC;

MODEL1:MODEL SYMP=AGE NCV SEX HT WT; [4.6.3]

or CATMOD

PROC CATMOD;

DIRECT AGE NCV HT WT;

MODEL1:MODEL SYMP=AGE NCV SEX HT WT/NOITER NOPROFILE; [4.6.4]

Fourth, each variable was removed from the above model [4.6.4] to check G values. For example, without age (AGE), PROC LOGISTIC;

MODEL1:MODEL SYMP=NCV SEX WT HT; [4.6.5]

After the fourth procedure, the selected model is Model SYMP = AGE NCV SEX WT. [4.6.6]

Fifth, interactions between variables in the model [4.6.6] were considered. The following statements define the interaction terms. DATA INT;SET CTS2; AGXNC=AGE*NCV; AGXSE=AGE*SEX; AGXWT=AGE*WT; NCXSE=NCV*SEX; NCXWT=NCV*WT; SEXWT=SEX*WT; PROC LOGISTIC DATA=INT;

Then, the significant interaction terms were selected using the following statements:

```
MODELA:MODEL SYMP=AGE NCV SEX WT
```

```
AGXNC AGXSE AGXWT NCXSE NCXWT SEXWT; [4.6.7]
```

RUN;

PROC LOGISTIC DATA=INT;

MODEL5: MODEL SYMP=AGE NCV SEX WT AGXNC / CTABLE; [4.6.8]

4.6.3 Results and Conclusion

In univariate analysis, variables which had a p-value <0.25 were selected (see Table 4.9). These variables are significant to symptom (SYMP): AGE, NCV, SEX, HT, and WT.

Variable	p value <0.25
AGE	0.0104
NCV	0.0019
SEX	0.05564
НТ	0.2480
WT	0.1297

Table 4.9 Variables with p-value < 0.25

Stepwise variable selection in the LOGISTIC procedure suggests that NCV, SEX, and WT are significant to SYMP. In multivariate model and removed variable model selections, AGE, NCV, SEX, and WT are significant to symptom (SYMP).

Considering interactions, the result is shown in Table 4.10. The interaction (p value < 0.20) SEX * WT should be included in the model. In the final model, AGE, NCV, SEX, WT and SEX*WT will be included. These variables and interaction are significant in accounting for the behavior of the variable symptom.

The multiple logistic regression shows the estimated probability of an event as follows:

$$p = \frac{\exp(g(p))}{1 + \exp(g(p))},$$
 [4.6.9]

where

$$g(p) = 7.2291 + (-0.0196) * AGE + (-0.6884) * NCV + 0.6537 * SEX$$

+ (-0.0210) * WT + 0.0156 * SEX * WT [4.6.10]

The classification percentage for the five testing sets were 78%, 76%, 80%, 74%, and 76% (for a probability level of 0.70). The average is 76.8%, which is close to 79% from the classification procedure of logistic regression (see Equation 4.6.8).

included interaction	-2LOGL	G value	p value
main	212.360		
AGE * NCV	212.286	0.074	0.7840
AGE * SEX	212.058	0.032	0.5847
AGE * WT	211.219	1.141	0.2942
NCV * SEX	212.359	0.001	0.9716
NCV * WT	212.041	0.319	0.5761
SEX * WT	210.199	2.161	0.1476

Table 4.10 G values and p values of Interaction Terms

4.7 Experimental Design Procedure with Data Set B (n=252)

4.7.1 Purpose

The purpose of this procedure is to use analysis-of-variance model and find correlations between classification variables and continuous variables.

4.7.2 Preparation

All the continuous variables versus all the classification variables were tried in one statement. However, a limitation in memory for the mainframe system was encountered.

Therefore, continuous variables (one at a time) versus classification variables (two at a time with interaction term) was performed for all possible cases. The following is an example:

- continuous variable (AGE) .VS. classification variable (DOM SEX DOM*SEX):

PROC GLM DATA=CTS;

CLASS DOM SEX;

MODEL1:MODEL AGE=DOM | SEX; [4.7.1] RUN;

Continuous variables (all) versus classification variables (one at a time) was performed for all possible cases. The following is an example:

- continuous variable (AGE NCV YRS HT WT) .VS. classification variable (ALC):

PROC GLM DATA=CTS;

CLASS ALC;

MODEL104:MODEL AGE NCV YRS HT WT=ALC; [4.7.2] RUN;

Continuous variables (one at a time) versus classification variables (all) was performed for all possible cases. The following is an example: - continuous variable (NCV) .VS. classification variable (DOM SEX VIT ALC OCC SMO):

PROC GLM DATA=CTS;

CLASS DOM SEX VIT ALC OCC SMO;

MODEL1:MODEL NCV=DOM SEX VIT ALC OCC SMO; [4.7.3] RUN;

4.7.3 Results and Conclusion

Type III error and its p value is a common tool to decide the significance of a treatment or classification variable to the continuous variable (response). The results show that: SYMP, SEX, and VIT are significant to NCV. SYMP and ALC are significant to AGE. OCC and SMO are significant to HT.

SYMP, SEX, and ALC are significant to WT.

Of these, SYMP, SEX, and VIT are important factors in accounting for the variable NCV.

4.8 Summary and Conclusion

For nerve conduction time, linear regression was used. Other models can be considered for further study. For example, polynomial regression can be considered for modelling.

In statistical procedure or analysis, there are two logics on which analysis is based: scientific logic (hypothesis) and statistical logic. Scientific logic provides the interest and direction of research. In this analysis, nerve conduction time and symptom may be related to or accounted for by other independent variables. After the statistical procedures, certain scientific logic were partially proven. During the procedures, statistical logic provides the selection and decision of variables and models. However, some of the results (for example, correlation between smoking and surgery) are irrelevant and meaningless in term of scientific logic. This analysis has the advantage of finding the significant variables for an indicator - NCV and SYMP, and the best fit model. Also, it can provide the basis for assigning membership values for the aggregation of a fuzzy operator. In the next two chapters, we present two other modelling methods that were studied for quantifying the relationship between variables and predicting the incidence of CTS.

CHAPTER 5

BACK PROPAGATION OF NEURAL NETWORK

5.1 Introduction to Neural Network

Artificial neural network is one of the research areas for artificial intelligence. Rule-based expert systems have been very popular artificial intelligent models for human decision making. However, the vast efforts to understand human intelligence and implement intelligence in machines brought another point of view to researchers. Researchers studied the neurons and the mechanism of brain from a biological point of view. The mechanism of the brain is that neurons are inter-connected and send electrical signals (impulses) to each other. If the sum of signals exceeds the threshold, a neuron fires a signal to the next neuron.

Kohonen gave the following definition of artificial neural network like this [Kohonen, 1988]: Artificial neural networks are massively parallel interconnected networks of simple (usually adaptive) elements and their hierarchical organization which are intended to interact with the objects of the real world in the same way as biological nervous systems do.

There are three fundamental descriptors for neural networks [Masson, 1990]: Architecture, transfer function and learning law.

Based on these three descriptors and their researchers, neural networks can be characterized and named differently. Those networks are Perceptrons, Hopfield network. Boltzmann machine, Selforganizing networks and Back propagation network. The applications of these neural networks include pattern recognition, knowledge data bases for stochastic information, optimization computations, robot control and decision making.

One of the neural networks for pattern classification and function approximation is the back propagation learning procedure or network. This network has a multilayer architecture and uses a combined method of minimizing mean squared error and gradient descent procedure to train weights of units in its structure.

5.2 Introduction to the Back Propagation Network (Procedure)

The back propagation network is multilayered with three classes of units: input units, ouput units and hidden units. Input units receive the input patterns directly from outside of the network. Output units have associations with target input and actual output. Hidden units exists between input units and output units. In Figure 5.1, the typical structure of a back propagation network is shown. The first layer from the bottom is the input unit layer, and the top layer is the output unit layer. Between those two layers, hidden unit layers are connected to the input layer and output layer with weights and biases. The weights among units can be determined or trained by effective most-error

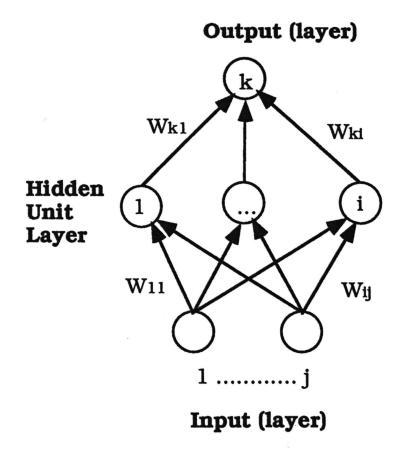


Figure 5.1 Back Propagation Network

reducing procedures which are called Least Mean Square (LMS) and gradient descent procedures. The objective of this network is to find a set of weights that minimize the error between the desired output (t_{pi}) and the actual output (O_{pi}) . As a measurement of this objective, the summed square error function is used,

$$E = \sum_{p} E_{p} = \sum_{p} \sum_{i} (t_{pi} - O_{pi})^{2}.$$
 [5.1]

where

p is the number of input patterns, i is the number of input units, and E_p is the error on pattern p.

The next step is to find and update the set of weights which minimize the error function. The back propagation procedure uses the gradient descent method which changes the weight proportional to the negative of the derivative of the error or the error function,

$$\Delta w_{ij} = -k \frac{\partial E_P}{\partial w_{ij}}, \qquad [5.2]$$

where k is the constant of proportionality. The equation 5.2 can be derived to equation 5.3 with proper nonlinear function and differentiation.

$$\Delta w_{ij} = \varepsilon \delta_{pi} a_{pj} \,. \tag{5.3}$$

The change of weight should be proportional to the product of a term called δ_{pi} and the activation, a_{pj} . δ_{pi} is the effect of a change in the net input to unit j on the output of unit i in pattern p. ϵ is the learning rate parameter. If a unit is an output unit, δ_{pi} is presented as,

$$\delta_{pi} = (t_{pi} - a_{pi})f'(net_{pi})$$
[5.4]

where $net_{pi} = \sum_{i} w_{ij}a_{pj} + bias_i$ and $f'_i(net_{pi})$ is the derivative of the activation function. The bias_i is the weight or threshold from unit i when unit i is activated. If the unit is not an output unit,

$$\delta_{pi} = f'_i(net_{pi}) \sum_k \delta_{pkWki}$$
[5.5]

The back propagation learning has two phases: Propagate forward through the network to compute the output value a_{pj} for each unit, and propagate backward to compute δ . After these two phase, the weight error derivative can be computed.

As the activation function, the logistic activation function is used,

$$a_{pi} = \frac{1}{1 + e^{-net_{pi}}}.$$
 [5.6]

The derivative of this function is

$$\frac{da_{pi}}{dnet_{pi}} = a_{pi}(1-a_{pi}).$$

$$[5.7]$$

Therefore, the error signal, δ_{pi} , for an output unit is

$$\delta_{pi} = (t_{pi} - a_{pi})a_{pi}(1 - a_{pi}),$$
 [5.8]

and the error for a hidden unit is

$$\delta_{pi} = a_{pi}(1 - a_{pi}) \sum_{k} \delta_{pk} w_{jk}.$$
[5.9]

5.3 Description of Back Propagation Software

Based on the above back propagation learning rule, Dr. McClelland and Dr. Rumelhart provided a back propagation program in their book "Explorations in Parallel Distributed Processing - A Handbook of Models, Programs, and Exercise." The program was written in C language and compiled in PC version C. In addition to the execution file (bp.exe), this program requires three files: network file (.net) about the structure of network, template file (.tem) for display of the learning process and results, and starting file (.str) to state parameters and pattern file name.

The network file states the total number of units, numbers of input units and output units, connection between layers, and the values of biases. The template file specifies the appearance of the display screen and the variables. The starting file gives the network file, pattern file, random number seed, learning rate, and momentum. In the pattern file, the pattern name, input values and target values are included.

There are several variables which should be determined by the user: nepochs, ecrit, lrate, momen, tmax, and wrange, etc. The descriptions of these variables are as follows: nepochs : the number of processing cycles ecrit : the error value of stopping process lrate : the learning rate parameter momen : the value of the momentum parameter tmax: the target activation wrange : the range of variability for random weights More descriptions in details are explained in the book [McClelland &

Rumelhart, 1988].

Two major experiments were prepared for function approximation and pattern classification. Nerve conduction time (NCV) was considered as an output from the functions of symptom, age, dominant hand, sex, vitamin use, alcohol consumption, occupation, year in the current job, smoking, height, weight, arthritis, and surgery. The purpose of this first experiment was to demonstrate the learning ability of the back propagation network for function approximation. A second experiment was done to show the classification ability of back propagation as applied to the CTS symptom.

The Jack and Knife procedure used for validation in this study divides the data set into five sub-sets which contain 20 % of its original set, exclusively. The selection of the pattern that will go into each sub-set was done randomly. Then, one sub-set was considered as

the testing set, while other four sub-sets were combined as the training set. Therefore, there will be five different training sets and five different testing sets, exclusively. After training the network with a training pattern, the network was tested against the testing pattern. The performance rate (or correctness) was calculated and interpolated as the validation of the network (or the proposed model).

5.4 Function Approximation for NCV time and Jack & Knife procedure - two differnt data sets and six networks of different numbers of hidden units)

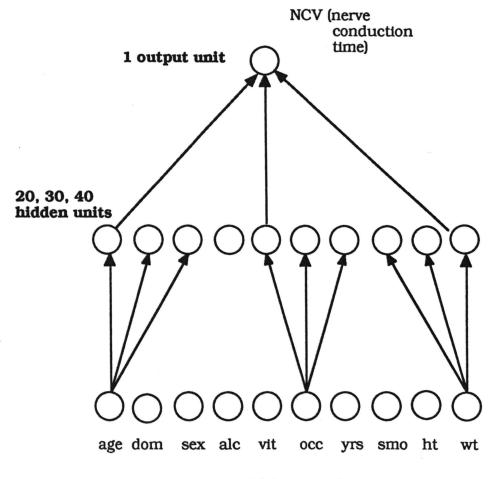
This experiment was prepared for comparison with the statistical linear regression. In the linear multiple regression of Chapter 4, the statistical analysis provided the significant independent variables. However, the selected independent variables could account for only 20 % of the dependent variable phenomena. Even though the back propagation network can not indicate the significance, it can approximate the value of the dependent variable from the independent variables. Also, the back propagation network does not require the consideration of any iteraction between the independent variables, nor the linearity of function between independent variables and dependent variables. If the concern in carpal tunnel syndrome is to predict nerve conduction time which can be used as an indicator of the incidence of CTS, the back propagation network can be a useful method for approximating nerve conduction time.

First, the experiments were prepared using Data Set A and Data Set B from the statistical analysis. Data sets were normalized to the range of [0,1]. Three networks, with varying number of hidden units, were prepared and trained with Data Set A and Data Set B. For Data Set A, the number of input (units) was ten. The number of output unit was one. The numbers of hidden units were 20, 30, and 40 (see Figure 5.2). Each network was trained at lrate = 0.01, momen = 0.85 and stopped at ecrit = 0.0152 [McClelland and Rumelhart, 1988]. The networks were trained successfuly with this error rate (see Table 5.1). The criterion for determination was a difference between target and actual output of 0.02. If the difference was greater than 0.02, it was considered to be in error. If pss value was greater than 0.0004, the networks could not learn that pattern easily.

For Data Set B, the ecrit was 0.0252, and the number of hidden units were 30, 40, and 50. The number of input units was 13 (see Figure 5.3). Other conditions were the same as in the training of Data Set A. The result is shown in Table 5.2. It almost learned 97% of patterns.

Then, using the Jack and Knife procedure with Data Set C (n=250), the experiment was prepared and performed. The number of hidden units is 30. The network is shown on Figure 5.4. The weights and biases of the network were saved to the weight file after every 20,000 nepochs. The weight file which represents correctness in testing ensures proper training - neither undertrained nor overtrained. The results, using properly trained weight file, are shown

Experiment A

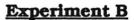


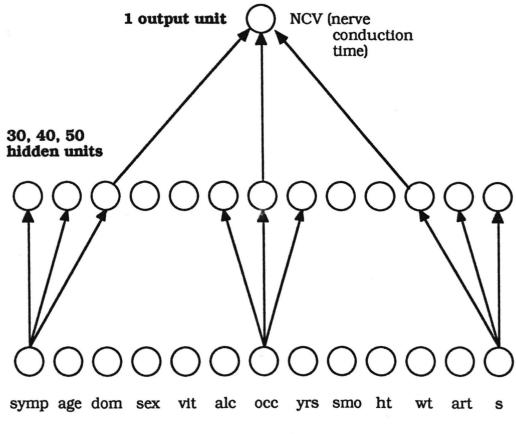
10 input units



Data Set	Data Set A					
No. of	hidden	No. of patterns	No. of untrained	Percentage (%)		
units			patterns	of training		
20		152	5	96.7%		
30		152	2	98.7%		
40		152	3	98.0%		

Table 5.1 Percentage of Training with Data Set A





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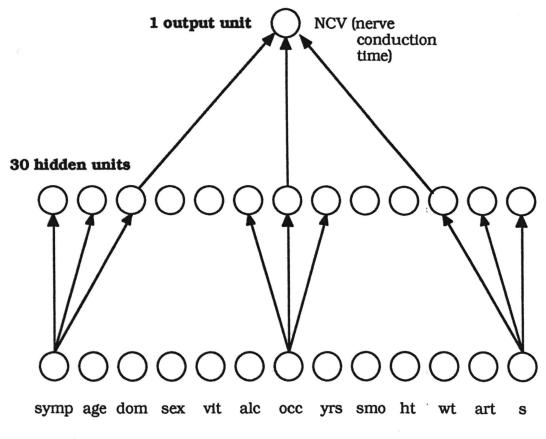
13 input units



Data Set B					
No. of hid units	den No. of patterns	s No. of untrained patterns	Percentage (%) of training		
30	252	8	96.8%		
40	252	9	96.4%		
50	252	6	97.6%		

Table 5.2 Percentage of Training with Data Set B

Experiment C



13 input units

5.4 Layout of Network for NCV Approximation (Jack and Knife Procedure)

in Table 5.3. Average correctness of test sets was 87.2 %. The average TSS (total sum of square over the patterns) value per pattern is 0.02514 (see Table 5.4).

5.5 Classification of Symptoms and Jack & Knife procedure

In this experiment, the pattern classification of back propagation network was presented with Data Set C. There were two patterns to be classified: whether the participant has symptom or not based on his/her natural, habitual, medical characteristics and nerve conduction time.

This network has 13 input units, 30 hidden units and 2 output units. The network is shown in Figure 5.5. It has been trained under the same conditions of the previous experiments. The decision of correctness in the trained network is that if the desired output is greater than the threshold (=0.7) and other output is less than 0.3, it is counted as the correct one. The Jack and Knife procedure was used for training and testing of network. The results are shown in Table 5.5. The average correctness is 76.0 %.

5.6 Conclusion and Disccusion

The back propagation network can learn presented patterns and approximate the function and classify the patterns into desired categories. In function approximation, it had an 87.2 % accuracy. In

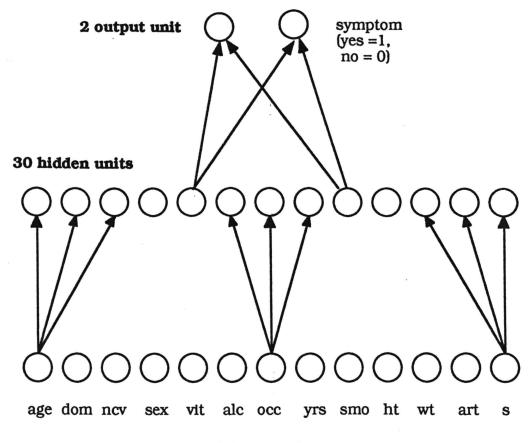
Table 5.3 Performance Rate of Function Approximation for NCV with Data Set C

Data Set	С	n=250				
Name of	No. of	Percenta	Name of	No. of	No of	% of
train set	training	ge(%) of	test	testing	error in	correct
	patterns	training	. *	patterns	testing	ness
train 1	200	83.0%	test 1	50	4	92%
train 2	200	89.5%	test 2	50	11	78%
train 3	200	87.5%	test 3	50	4	92%
train 4	200	72.5%	test 4	50	8	84%
train 5	200	90.5%	test 5	50	5	90%

Test Set	TSS	Average TSS
1	1.126	0.02252
2	1.600	0.03200
3	1.306	0.02612
4	1.197	0.02394
5	1.056	0.02112

Table 5.4 Average TSS of Test Sets

Experiment D



13 input units

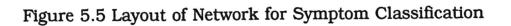


Table 5.5 Performance Rate of Classification for Symptom with Data Set C

Data Set C n=250						
Name of	No. of	Percenta	Name of	No. of	No of	% of
train set	training	ge(%) of	test	testing	error in	correct
	patterns	training		patterns	testing	ness
train 1	200	97.0%	test 1	50	13	74%
train 2	200	98.5%	test 2	50	11	78%
train 3	200	99.0%	test 3	50	14	72%
train 4	200	98.5%	test 4	50	12	76%
train 5	200	99.0%	test 5	50	10	80%

pattern classification, the accuracy is 76.0 %. In Data Set C, 45 out of 250 patterns had CTS symptom. When training set and testing set are created in Jack & Knife procedure, it is necessary to check whether the patterns of symptom are properly distributed between training set and testing set. The distribution of those patterns can affect the accuracy of the network. Also, these accuracies can be improved by designing a better network with the correct parameters. These correct parameters can be determined from an experiment on parameter sensitivity. However, the model could not define the relationships nor measure the significance between the input variables and the output variable.

CHAPTER 6

FUZZY OPERATOR AND AGGREGATION

6.1 Introduction to Fuzzy Set Theory and Operator

In our world, absolute truth or fact may exist and human being are always searching for the absolute truth or fact. The descriptions of those truth or fact is called information which can be generated or created by many different measurements and points of view. Since the beginning of civilization, the amount of information has soared beyond our capability to process, and various measurements and points of view about the same object or absolute truth have been developed. In addition to this complexity, the limits of knowledge and handling of the information has become a major concern and interest.

Researchers started to study about that aspect of human intelligence and function. The mechanism of intelligence in handling uncertainty may not be based on the crisp set theory. The crisp set theory is if element 'c' does not belong to set 'A', it should be belong to the complement of set 'A', A^C. In contrast to the crisp set theory, fuzzy set theory states that even if element 'c' does not belong to set 'A', it does not necessary belong to the complement of set 'A'. Fuzzy set theory provides grades of membership and non-membership. For example, the possible grade of membership to set 'A' is 0.7 and the possible grade of non-membership is 0.5. The membership grade is

bigger than the non-membership grade. This can be understood as element 'c' has greater plausibility of being a member of set 'A'. Crisp set theory is a restricted case of general fuzzy set theory. The membership grade will be 1.0 and the non-membership grade will be 0.0 in crisp set theory.

In fuzzy set theory, the membership grade or function is mathematically assigned between 0.0 and 1.0. Every element has its own membership values in the range of [0,1]. For example, there are four different elements (20's, 30's, 40's, and 50's in age) and three sets (young, a little old, and old). For some in 20's, the membership function can assigned like this: 0.9 for young, 0.2 for a little old, and 0.1 for old. Figure 6.1 shows the membership function of elements.

As mentioned above, the information is not single, but a set of multiple descriptions for final decision making. In other words, how to aggregate those informations into a final decision is our interest. Researchers have developed various tools and technique in fuzzy set theory. One of tools is called 'fuzzy connectives or operator.' These operators are similar to the aggregation of information in the human brain. There are three major operators: 1) Union operator, 2)Intersection operator, 3) Compensative operator. These three operators are classified by their behavior.

In the union operator, the aggregated value is high when any input values is high. In the intersection operator, the aggregation value is high only when all input variables are high. In the Compensative

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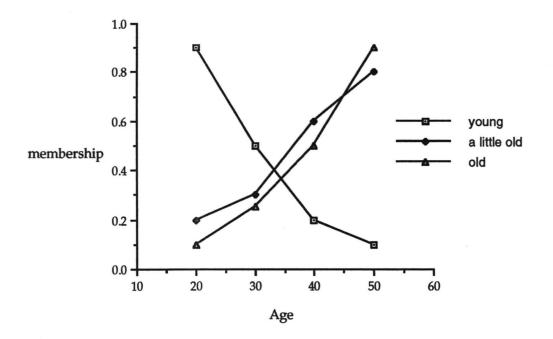


Figure 6.1 Fuzzy Membership .vs. Age

operator, the value will be sacrified a little on one factor and compensated by another factor. For the compensative operator, a general mean operator has been selected and presented for the implementation in aggregation among stress, indicator, and durability. The use of a general mean operator for aggregation is discussed in [Krishnapuram & Lee, 1992].

One of the attractive compensative operators is the generalized mean operator proposed by Dujmovic and later Dyckhoff and Pedrycz [1984]. The generating function of this operator is x^p . The definition of this operator is as follows;

The generalized mean of n-arguments $x^1, x^2, \dots, x^n \in [0,1]$ is a function $g_p : [0,1]^n \rightarrow [0,1]$ defined by

$$g_{p}(x_{1}, x_{2}, ..., x_{n}; w_{1}, ..., w_{n}) = \left(\sum_{i=1}^{n} w_{i} \chi_{i}^{p}\right)^{1/p},$$

where $p \in \mathbf{R}$ ($p \neq 0$), and $w_i \geq 0$ for i = 1, 2, 3, ..., n) are parameters, with $\sum_{i=1}^{n} w_i = 1$.

This general mean operator has the property that the operator is continuous with respect to p, and has the following values at infinity:

- 1) $\lim_{p\to\infty} g_p(x_1, x_2, x_3, ..., x_n) = \max(x_1, x_2, ..., x_n).$
- 2) $\lim_{p\to\infty}g_p(x_1,x_2,x_3,...,x_n)=\min(x_1,x_2,...,x_n).$
- 3) $\min(x_1, x_2, ..., x_n) \le g_p(x_1, x_2, x_3, ..., x_n) \le \max(x_1, x_2, ..., x_n)$.

The aggregation by the generalized mean operator is controlled by the values of w_i and p. Moreover, one can consider the w_i as representing relative the importance for the input x_i , and p can be treated as a parameter to control the degree of compensation between maximum and minimum. Figure 6.2 shows the generalized mean at different values p and w_i , and Figure 6.3 illustrates the range for varying p with fixed inputs.

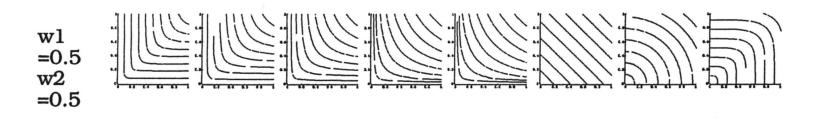
6.2 Fuzzy Aggregation and Suggested Assumptions

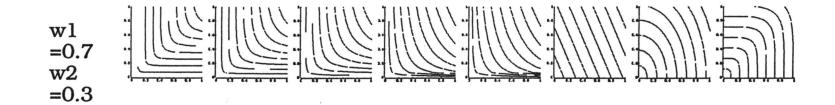
As discussed in Chapter 3, the concept of fuzzy aggregation and fuzzy operator, especially the general mean operator, can be implemented into the assumption about stress, indicator, and durability. The structure of the aggregation is shown in Figure 6.4.

Age, hand dominance, sex, height, and weight are put together and aggregated into natural durability. Vitamin use, alcohol consumption and smoking are aggregated into habitual durability. Arthritis and surgery are aggregated into medical (or clinical) durability. Then, the three durabilities are aggregated into final durability. Occupation and years on the current job are aggregated into stress measurement. Symptom and nerve conduction time are aggregated into indicator. An assumption is made that the relationship between stress, durability and indicator is linear, where final durability minus stress is equal to one minus indicator. This assumption was presented in section 3.3 and illustrated in Figure 3.5 and Figure 3.6.

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p = -5.0 -2.0 -1.0 -0.1 0.1 1.0 2.0 5.0





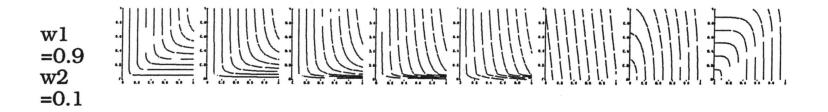


Figure 6.2 Behavior of General Mean Operator

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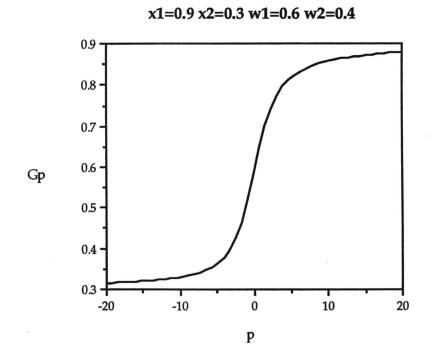


Figure 6.3 Behavior of General Mean Operator upon p value

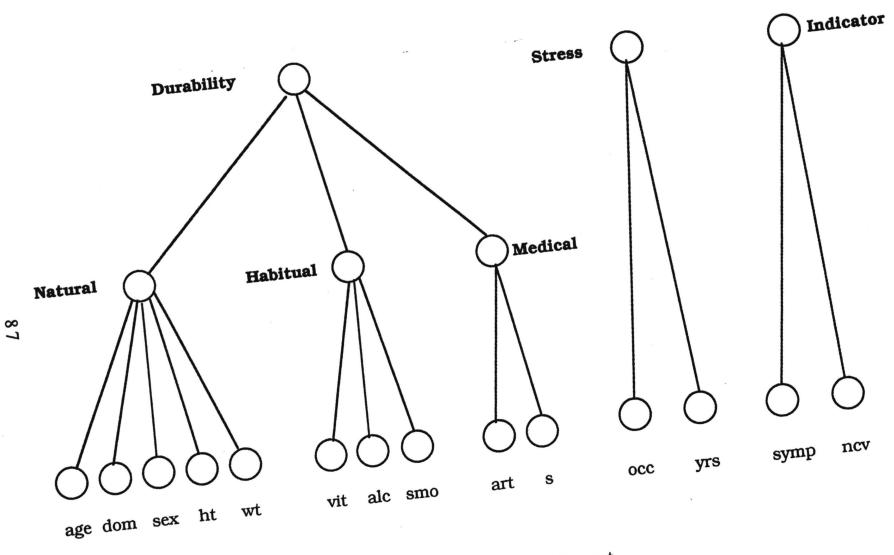


Figure 6.4 Hierachical Layout

The parameter 'w' and the input values were assigned based on literature review and statistical analysis. The assignment of 'w' values was as follows:

- Natural durability

 $w_{n1} = 0.4$: Age $w_{n2} = 0.1$: Dominant hand $w_{n3} = 0.3$: Sex

 $w_{n4} = 0.1$: Height

 $w_{n5} = 0.2$: Weight

- Habitual durability

 $w_{h1} = 0.2$: Vitamin use

 $w_{h2} = 0.5$: Alcohol consumption

 $w_{h3} = 0.3$: Smoking

- Medical durability

 $w_{m1} = 0.6$: Arthritis

 $w_{m2} = 0.4$: Surgery

- Durability

 $w_{d1} = 0.3$: Natural durability

 $w_{d2} = 0.1$: Habitual durability

 $w_{d3} = 0.6$: Medical durability

- Stress

 $w_{s1} = 0.3$: Occupation

 $w_{s2} = 0.7$: Years on the job

- Indicator

 $w_{i1} = 0.4$: Symptom

 $w_{i2} = 0.6$: Nerve conduction time

- Age (AGE)

normalized to the range of [0,1]

```
- Dominant hand (DOM)
```

```
yes = 0.9
```

no = 0.8

- Sex (SEX)

male = 0.80

female = 0.65

- Height (HT)

normalized to the range of [0,1]

- Weight (WT)

normalized to the range of [0,1]

- Vitamin use (VIT)

yes = 0.7

no = 0.8

- Alcohol consumption (ALC)

```
yes = 0.9
no = 0.8
```

- Smoking (SMO)

```
yes = 0.9
```

$$no = 0.8$$

- Occupation (OCC)

bushing operator = 0.8 winding operator = 0.8 creel operator = 0.8 packer/ inspector = 0.8 data entry clerk/ secretary = 0.7

laboratory technician = 0.4

engineer/ system analyst = 0.3

- Years on the job (YRS)

normalized to the range of [0,1]

- Symptom (SYMP)

yes = 0.18

no = 0.82

- Nerve conduction time (NCV)

normalized to the range of [0,1]

The program has been tested for finding proper 'p' values in the network. Eleven different p values (-5, -4, -3, -2, -1, 0.01, 1, 2, 3, 4, 5) were tested for each p value. Then, the squares of error in each pattern was summed up, and the total sum of square error was used to find the best combination of p values.

6.3 Simulation Results

The smallest total of squared error was 7.8382 at ps = -5.0, pi = -1.0, pn = 5.0, ph = 5.0, pm = 5.0 and pd = 5.0. Based on those p values, the values of durability, stress, and indicator were calculated and counted as an error if the difference was bigger than 0.1.

6.4 Combined with Back Propagation Training

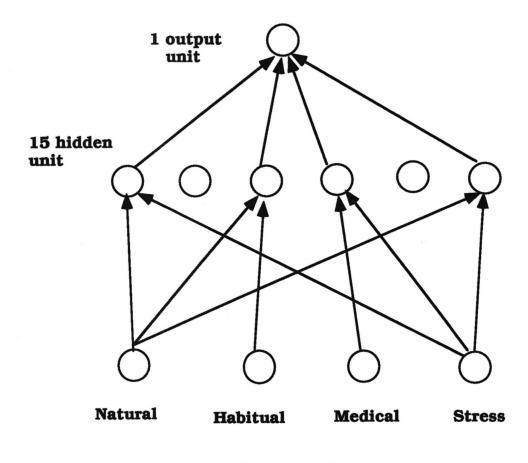
In the previous section, the assumption was made of a linear relationship between stress, durability and indicator. The assumption causes the p values to have the values shown above. A smaller p value is better for reducing stress because a smaller or negative p value will compensate strongly between minimum and maximum values. A bigger p value is better for increasing durability because it will increase the final value of durability. However, if the relationship is not a linear one, we may use a back propagation network to determine the relationship in presented patterns, and to predict the output based on a trained network. Back propagation and the Jack and Knife procedure were used in this study.

Four input units (natural, habitual, medical durability and stress) and fifteen hidden units are prepared for the network. One output unit was set up for the indicator (see Figure 6.5). The patterns were calculated by fuzzy aggregation operators. Two sets of patterns were prepared with previous p values and intuitively assigned p values.

The parameters of the back propagation network were as follows; ecrit = 0.02 lrate = 0.001 mom = 0.85

The results of Jack and Knife procedure are shown in Table 6.1.

Indicator



4 input unit

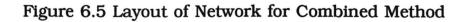


Table 6.1 Performance Rate of Combined Method with Data Set C	Table 6.1	Performance	Rate o	of Combined	Method	with	Data	Set (С
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Data Set C n=250						
Name of	No. of	Percenta	Name of	No. of	No of	% of
train set	training	ge(%) of	test	testing	error in	correct
	patterns	training		patterns	testing	ness
train 1	200	75.5%	test 1	50	14	72.0%
train 2	200	78.5%	test 2	50	13	74.0%
train 3	200	78.5%	test 3	50	13	74.0%
train 4	200	71.0%	test 4	50	6	88.0%
train 5	200	70.0%	test 5	50	15	74.5%

The average correctness is 76.5 %. In other words, the output, 'indicator of CTS' was predicted with 76.5 % accuracy.

6.5 Conclusion and Discussion

The proposed model, which was trained with the back propagation method after being aggregated by the general mean operator, predicts the severity of CTS with 76.5 % accuracy. The accuracy of this model may be different or improved by assigning other values to w, p, and inputs, and designing a different network structure.

CHAPTER 7

CONCLUSION

7.1 Summary of Thesis

The interests in this study were to understand the relationships between variables, independent variables and dependent variables or inputs and outputs, and the capability to predict the incidence of OCTS. Three different methods were used to satisfy these interests. Using statistical procedures, multiple linear regression showed that symptom, vitamin use, and weight were important factors to account for nerve conduction time. The multiple linear regression model was tested with five test sets of 50 samples each. The performance percentages were 22%, 18%, 38%, 20%, and 20% (considered correct if the difference between the actual value and the predicted value is less than 0.152). The average was 23.6% which is a very low performance percentage for the prediction of nerve conduction time. Other regression models such as polynomial regression should be considered in future studies to account for nerve conduction time. The multiple logistic regression procedure showed that nerve conduction time, sex, and weight are significant variables for the CTS symptom. For the predicted probability of an event, age, nerve conduction time, sex, weight, and interaction between age and weight were included in the model. The classification percentages of five test sets were 78%, 76%, 80%, 74%, and 76% (the probability level is 0.70). The average

is 76.8% which is similar to 79% from the classification procedure of logistic regression.

The back propagation network, using the Jack and Knife procedure for the validity of the network showed that the average performance percentages were 87.2% and 76.0% for the function approximation of nerve conduction time and the classification of symptom, respectively. The combined method, aggregated by general a mean operator and trained by the back propagation procedure, showed a performance percentage of 76.5%. The performance percentages can be improved by designing different network structures and selecting proper parameter values.

7.2 Strength and Weakness of Model and Implementation Methods

The back propagation network does not require the consideration of the interactions and the elimination of variables. It can learn the characteristics of the patterns which consist of inputs and outputs. The learning of the back propagation network can be used to predict the outputs: nerve conduction time and symptom. However, in the design and training of the network, there is no absolute rule or guideline to follow. The training may result in time consuming and low performance rate. Fuzzy aggregation by a general mean operator provides the chance to aggregate variables in desired categories: natural, habitual, medical durability, stress, and indicator. However, it can not provide a ranking of the importance of variables. In this study, the decision of 'w' and 'p' values was based on the result

of the statistical procedure and the literature review. The combined method supports and satisfies the assumptions which were proposed in Chapter 3: three quantifiable areas, and the aggregation of the evidence in each quantifiable area and between the three areas. This combined method can be used to predict the likelihood of the incidence of OCTS. This method has the advantage of including the concept of fuzzy set theory and the training capability of back propagation. Statistical procedures have the advantage of finding significant independent variables that affect a dependent variable. However, statistical procedures can not support the aggregation which was proposed in Chapter 3. A direct comparison of the results from each method is difficult because the performance percentage of each method is affected by the data sets used, and technical detail, e.g., selecting models, choosing parameter values.

In the implementaion of the methods developed, the collected data of persons - symptom, age, dominant hand, nerve conduction time, sex, vitamin use, alcohol consumption, occupation, years in present job, smoking, height, weight, arthritis, and surgery or broken bones - can be put into these models for prediction of OCTS. However, the collected data should be in the range of the original data set. For example, the range of age in Data Set C is from 22 to 60. If the age of person is 20 or 63, the model will not be suitable for use. Better prediction will be possible when additional data are collected with properly divided categories. For example, the concept of female and male in gender category may be divided into size of wrist, strength of tendon, etc.

7.3 Future Study

As mentioned above, the decision on parameter values in the back propagation network and fuzzy aggregation operator should be studied more for making the proper basis and assigning reasonable values to parameters. The collection of data should be designed to support this combined method. In past studies, the binary responses of variables, e.g., smoking, and vitamin use, were surveyed. This data collection procedure can be designed to include the concept of fuzzy set theory and to be more specific, e.g., how many cigarettes were smoked, and how often were vitamins taken? Because the list of survey contents can be different based on the interest of researchers, the NIOSH should consider specifying the guidelines for the full lists to be surveyed, and making the data base generally accessible.

REFERENCES

[1] Armstrong, T.J. and Chaffin, D.B., "Some Biomechanical Aspects of the Carpal Tunnel", *Journal of Biomechanics*, Vol.12, pp.567-570, 1979.

[2] Amstrong, T.J., Foulke, J.A., Joseph, B.S. and Goldstein, S.A.,
"Investigation of Cumulative Trauma Disorders in a Poultry Processing Plant", *American Industrial Hygiene Association Journal*, Vol.43, No.2, pp. 103-116, 1982.

[3] Barrer, S.J., "Gaining the Upper Hand on Carpal Tunnel Syndrome", *Occupational Health & Safety*, pp. 38-43, 1991.

[4] Burt, S., "Carpal Tunnel Syndrome among Employees at a Window Hardware Manufacturing Plant", *Aaohn Journal*, Vol.39, No.12, pp. 576-577, 1991.

[5] Dawson, D.M., Hallett, M. and Millender, L.H., "Entrapment Neuropathies", Boston: Little, Brown and Co., pp. 5-59, 1983.

[6] Delgrosso, I. and Boillat, M.A., "Carpal Tunnel Syndrome: Role of Occupation", *International Archives of Occupational Environmental Health*, Vol.63, pp. 267-270, 1991.

[7] Dyckhoff, H. and Pedrycz, W., "Generalized Means and as a Model of Compensation Connectives", *Fuzzy Sets and Systems*, Vol.14, No.2, pp. 143-154, 1984.

[8] Feldman, R.G., Travers, P.H., Chirico-Post, J. and Keyserling, W.M., "Risk Assessment in Electronic Assembly Workers: Carpal Tunnel Syndrome", *Journal of Hand Surgery*, Vol.12a, pp. 849-855, 1987.

[9] Fischer, B.D., White, B.E., and Wygant, R.M., "Wristress. A Computerized System for Measuring Wrist Stress", *Computers & Industrial Engineering*, Vol.19, pp. 341-345, 1990.

[10] Fisher, D.L., Andres, R.O., Airth, D. and Smith, S., "Carpal Tunnel Syndrome: The Design of Optimal Rate-Rest Profiles", *Proceedings of the Human Factors Society 34th Annual Meeting-1990*, pp. 791-794, 1991.

[11] Franklin, G.M., Haug, J., Heyer, N., Checkoway, H. and Peck, N., " Occupational Carpal Tunnel Syndrome in Washington State, 1984-1988", *American Journal of Public Health*, Vol.81, No.6, pp. 741-746, 1991.

[12] Gelberman, R.H., Hergenroeder, P.T. and Hargens, A.R., "The Carpal Tunnel Syndrome: A Study of Carpal Canal Pressures", *Journal* of Bone Joint Surgery, Vol.36A, pp. 380, 1981.

[13] Gerwatowski, L.J., McFall, D.B. and Stach, D.J., "Carpal Tunnel Syndrome - Risk Factors and Preventive Strategies for the Dental Hygienist", *Journal of Dental Hygiene*, Vol.66, No.2, pp. 89-94, 1992.

[14] Grant, K.A., Congleton, J.J., Koppa, R.J., Lessard, C.S. and Huchingson, R.D., "Use Motor Nerve Conduction Testing and Vibration Sensitivity Testing as Screening Tools for Carpal Tunnel Syndrome in Industry", *Journal of Hand Surgery*, Vol.17a, pp. 71-6, 1992.

[15] Grant, K.A., Congleton, J.J. and Koppa, R.J., "Age and Weight Effects on Motor Nerve Conduction Time Measurement in an Asymptomatic Industrial Population", *Journal of Occupational Rehabilitation*, 1992.

[16] Hanrahan, L.P., Higgins, D., Anderson, H., Haskins, L. and Tai, S.,
"Public Health Project SENSOR: Wisconsin Surveillance of Occupational Carpal Tunnel Syndome", *Wisconsin Medical Journal*, pp. 80-83, 1991.

[17] Hosmer, D.W. and Lemeshow, S. "Applied Logistic Regression", John Wiley & Sons, Inc., New York, 1989.

[18] Kohonen, T., "An Introduction to Neural Computing", *Neural Networks*, Vol.1, pp. 3-16, 1988.

[19] Krishnapuram, R. and Lee, J., "Fuzzy-set-based Hierarchical Aggregation Networks for Decision Making", *Fuzzy Sets Syst.*, Vol.46, No.12, pp. 11-27, 1992

[20] Masson, E. and Wang, Y.J., "Introduction to Computation and Learning in Artificial Neural Networks", *European Journal of Operational Research*, Vol.47, pp. 1-28, 1990.

[21] McClelland, J.L. and Rumelhart, D.E., "Explorations in Parallel Distributed Processing - A Handbook of Models, Programs, and Exercises", MIT Press, 1988.

[22] Monsell,F.P. and Tillman, R.M., "Shearer's Wrist; The Carpal Tunnel Syndrome as an Occupational Disease in Professional Sheep Shearers", *British Journal of Industrial Medicine*, Vol.49, pp. 594-595, 1992.

[23] Moore, A., Wells, R., Ranney, D., "Quantifying Exposure in Occupational Manual Tasks with Cumulative Trauma Disorder Potential", *Ergonomics*, Vol.34, No.12, pp. 1433-1453, 1991.

[24] Morgan, S., "Most Factors Contributing to CTS Can be Minimized, if not Eliminated", *Occupational Health & Safety*, pp. 47-54, 1991.

[25]. Morgenstern, H., Kelsh, M., Kraus, J. and Margolis, W., "A Cross-Sectional Study of Hand/Wrist Symptoms in Female Grocery Checkers", *American Journal of Industrial Medicine*, Vol.20, pp. 209-218, 1991.

[26] Omer, G.E., "Median Nerve Compression at the Wrist", Hand Clinics, Vol.8, No.2, pp. 317-324, 1992.

[27] Rydevik, B., Lundborg, G. and Bagge, U., "Effects of Graded Compression on Intraneural Blood Flow", *Journal of Hand Surgery*, Vol.16A, pp. 191, 1991.

[28] Siebenaler, M.J. and McGovern, P., "Carpal Tunnel Syndrome -Priorities for Prevention", *Aaohn Journal*, Vol.40, No.2, pp. 62-71, 1992.

[29] Siverstein, B.A., Fine, L.J. and Armstrong, T.J., "Occupational Factors and Carpal Tunnel Syndrome", *American Journal of Industrial Medicine*, Vol.11, pp. 343-358, 1987.

[30] Skandalakis, J., Colborn, G.L., Skandalakis, P.N., McColliam, S.M. and Skandalkis, L.J., "The Carpal Tunnel Syndrome: Part-I", *American Surgeon*, Vol.58, No.1, pp. 72-76, 1992

[31] Stedt, J.D., "Interpreter's Wrist - Repetitive Stress Injury and Carpal Tunnel Syndrome in Sign Language Interpreters", *American Annals of the Deaf*, Vol.137, No.1, pp. 40-43, 1992.

[32] Tountas, C.P., Macdonald, C.J. and Meyerhoff, J.D., "Carpal Tunnel Syndrome: A Review of 507 Patients", *Minnesota Med*, Vol.66, pp. 478-482, 1983.

[33] Williams, T.M., Mackinnon, S.E., Novak, C.B., McCabe, S. and Kelly, L., "Verification of the Pressure Provocative Test in Carpal Tunnel Syndrome", *Annals of Plastic Surgeon*, Vol.29, pp. 8-11, 1992.

APPENDIX A

DATA SET A (N=152)

PART SYMP AGE DOM MED NCV SEX VIT ALC OCC YRS SMO HT WT ART S
58 0 33 1 0.74 4.83 1 0 1 1 3.50 0 72.0 190 0 0
58 0 33 0 0.40 5.20 1 0 1 1 3.50 0 72.0 190 0 0
60 0 41 1 0.50 3.90 1 0 1 1 6.00 0 69.0 175 0 0
60 0 41 0 0.54 3.10 1 0 1 1 6.00 0 69.0 175 0 0
61 0 29 1 0.60 3.70 1 1 1 1 4.00 0 72.0 165 0 0
61 0 29 0 0.50 4.03 1 1 1 1 4.00 0 72.0 165 0 0
63 0 31 1 0.66 3.77 1 0 1 1 1.50 1 69.0 185 0 0
63 0 31 0 0.71 3.60 1 0 1 1 1.50 1 69.0 185 0 0
65 0 40 1 0.59 4.20 1 0 1 1 1.50 1 70.0 190 0 0
65 0 40 0 0.65 3.98 1 0 1 1 1.50 1 70.0 190 0 0
66 0 32 1 0.53 3.95 1 0 1 1 6.00 1 71.0 220 0 0
66 0 32 0 0.45 3.46 1 0 1 1 6.00 1 71.0 220 0 0
68 0 31 1 0.30 3.60 0 1 1 1 2.00 0 67.0 155 0 0
68 0 31 0 0.45 3.67 0 1 1 1 2.00 0 67.0 155 0 0
70 0 39 1 0.70 3.63 1 0 0 0 4.25 1 73.0 170 0 0
70 0 39 0 0.63 3.25 1 0 0 0 4.25 1 73.0 170 0 0
72 0 26 1 0.60 4.48 1 1 1 1 1 1.00 0 77.0 195 0 0
72 0 26 0 0.75 4.35 1 1 1 1 1.00 0 77.0 195 0 0
73 0 40 1 1.20 3.78 1 0 0 0 5.00 0 73.0 190 0 0
73 0 40 0 0.76 3.56 1 0 0 0 5.00 0 73.0 190 0 0
74 0 29 1 0.60 3.88 0 1 0 1 2.00 0 64.0 155 0 0
74 0 29 0 0.45 3.80 0 1 0 1 2.00 0 64.0 155 0 0
75 0 32 1 1.28 3.78 0 1 0 0 9.00 1 64.0 105 0 0
75 0 32 0 0.80 3.75 0 1 0 0 9.00 1 64.0 105 0 0
77 0 28 1 0.60 4.23 0 0 1 1 2.50 0 68.0 147 0 0
77 0 28 0 0.38 3.40 0 0 1 1 2.50 0 68.0 147 0 0
78 0 33 1 0.51 3.63 0 0 1 1 11.00 0 66.0 135 0 0
78 0 33 0 0.49 3.90 0 0 1 1 11.00 0 66.0 135 0 0
80 0 44 1 0.66 3.90 1 0 0 0 11.00 0 72.0 185 0 0
80 0 44 0 1.01 4.00 1 0 0 0 11.00 0 72.0 185 0 0
82 0 22 1 0.55 3.60 1 0 1 1 2.50 0 73.0 225 0 0
82 0 22 0 0.58 3.70 1 0 1 1 2.50 0 73.0 225 0 0
85 0 53 1 1.00 4.38 1 1 0 1 14.00 1 72.0 164 0 0
85 0 53 0 0.86 4.00 1 1 0 1 14.00 1 72.0 164 0 0
86 0 26 1 0.50 3.95 1 0 0 1 7.00 0 72.0 190 0 0
86 0 26 0 0.61 3.68 1 0 0 1 7.00 0 72.0 190 0 0
88 0 31 1 0.64 4.00 0 0 1 0 3.00 0 64.0 148 0 0
88 0 31 0 0.78 4.00 0 0 1 0 3.00 0 64.0 148 0 0
90 0 33 1 0.33 4.83 1 0 0 1 1.50 0 67.0 160 0 0
90 0 33 0 0.35 4.44 1 0 0 1 1.50 0 67.0 160 0 0
92 0 36 1 0.54 3.60 0 0 0 1 11.00 0 62.0 138 0 0
92 0 36 0 0.58 3.47 0 0 0 1 11.00 0 62.0 138 0 0
93 0 28 1 0.85 3.20 1 0 1 1 2.00 0 63.0 128 0 0
93 0 28 0 0.78 3.20 1 0 1 1 2.00 0 63.0 128 0 0
94 0 30 1 0.81 4.14 1 0 0 1 7.00 0 67.0 244 0 0
94 0 30 0 0.71 3.84 1 0 0 1 7.00 0 67.0 244 0 0
95 0 46 1 0.69 3.50 0 1 0 1 3.50 0 66.0 180 0 0
95 0 46 0 0.46 3.75 0 1 0 1 3.50 0 66.0 180 0 0
102 0 25 1 1.10 3.93 1 0 1 1 4.00 1 71.0 240 0 0

APPENDIX B

DATA SET B (N=252)

PART SYMP AGE DOM MED NCV SEX VIT ALC OCC YRS SMO HT WT ART S
55 1 37 1 0.58 3.58 1 0 0 0 7.00 0 67.0 185 0 0
55 1 37 0 0.98 3.70 1 0 0 0 7.00 0 67.0 185 0 0
57 1 35 1 1.04 4.80 1 0 0 1 8.00 0 74.0 282 0 0
57 0 35 0 0.58 5.10 1 0 0 1 8.00 0 74.0 282 0 0
58 0 33 1 0.74 4.83 1 0 1 1 3.50 0 72.0 190 0 0
58 0 33 0 0.40 5.20 1 0 1 1 3.50 0 72.0 190 0 0
59 1 54 1 0.51 5.23 0 0 0 1 14.00 1 66.0 200 0 0
59 1 54 0 0.66 4.78 0 0 0 1 14.00 1 66.0 200 0 0
60 0 41 1 0.50 3.90 1 0 1 1 6.00 0 69.0 175 0 0
60 0 41 0 0.54 3.10 1 0 1 1 6.00 0 69.0 175 0 0
61 0 29 1 0.60 3.70 1 1 1 1 4.00 0 72.0 165 0 0
61 0 29 0 0.50 4.03 1 1 1 1 4.00 0 72.0 165 0 0
63 0 31 1 0.66 3.77 1 0 1 1 1.50 1 69.0 185 0 0
63 0 31 0 0.71 3.60 1 0 1 1 1.50 1 69.0 185 0 0
64 0 41 1 0.69 3.60 0 0 1 0 9.00 1 63.0 130 0 0
64 0 41 0 0.68 3.95 0 0 1 0 9.00 1 63.0 130 0 1
65 0 40 1 0.59 4.20 1 0 1 1 1.50 1 70.0 190 0 0
65 0 40 0 0.65 3.98 1 0 1 1 1.50 1 70.0 190 0 0
66 0 32 1 0.53 3.95 1 0 1 1 6.00 1 71.0 220 0 0
66 0 32 0 0.45 3.46 1 0 1 1 6.00 1 71.0 220 0 0
67 0 43 1 0.61 3.34 0 0 0 1 5.50 1 60.0 107 1 0
67 0 43 0 0.71 3.50 0 0 0 1 5.50 1 60.0 107 1 0
68 0 31 1 0.30 3.60 0 1 1 1 2.00 0 67.0 155 0 0
68 0 31 0 0.45 3.67 0 1 1 1 2.00 0 67.0 155 0 0
69 0 38 1 0.75 4.46 0 0 0 0 10.00 1 65.5 135 1 0
69 0 38 0 0.84 4.70 0 0 0 0 10.00 1 65.5 135 1 0
70 0 39 1 0.70 3.63 1 0 0 0 4.25 1 73.0 170 0 0
70 0 39 0 0.63 3.25 1 0 0 0 4.25 1 73.0 170 0 0
71 0 56 1 0.84 4.60 1 0 1 1 2.00 1 70.5 154 1 0
71 0 56 0 0.76 4.70 1 0 1 1 2.00 1 70.5 154 1 1
72 0 26 1 0.60 4.48 1 1 1 1 1.00 0 77.0 195 0 0
72 0 26 0 0.75 4.35 1 1 1 1 1.00 0 77.0 195 0 0
73 0 40 1 1.20 3.78 1 0 0 0 5.00 0 73.0 190 0 0
73 0 40 0 0.76 3.56 1 0 0 0 5.00 0 73.0 190 0 0
74 0 29 1 0.60 3.88 0 1 0 1 2.00 0 64.0 155 0 0
74 0 29 0 0.45 3.80 0 1 0 1 2.00 0 64.0 155 0 0
75 0 32 1 1.28 3.78 0 1 0 0 9.00 1 64.0 105 0 0
75 0 32 0 0.80 3.75 0 1 0 0 9.00 1 64.0 105 0 0
76 0 28 1 0.35 4.50 1 1 1 1 1.00 0 71.0 200 0 0
76 1 28 0 1.28 3.80 1 1 1 1 1.00 0 71.0 200 0 0
77 0 28 1 0.60 4.23 0 0 1 1 2.50 0 68.0 147 0 0
77 0 28 0 0.38 3.40 0 0 1 1 2.50 0 68.0 147 0 0
78 0 33 1 0.51 3.63 0 0 1 1 11.00 0 66.0 135 0 0
78 0 33 0 0.49 3.90 0 0 1 1 11.00 0 66.0 135 0 0
79 1 45 1 0.73 4.23 1 0 1 0 12.00 0 73.0 215 0 0
79 1 45 0 0.51 4.90 1 0 1 0 12.00 0 73.0 215 0 0
80 0 44 1 0.66 3.90 1 0 0 0 11.00 0 72.0 185 0 0
80 0 44 0 1.01 4.00 1 0 0 0 11.00 0 72.0 185 0 0
82 0 22 1 0.55 3.60 1 0 1 1 2.50 0 73.0 225 0 0

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